Building a Resilient Cancer Healthcare System Using Resources Management Reallocation:

A System Dynamics Modeling Approach

Thesis Submitted in Partial Fulfillment of the Requirements

for MPHIL in System Dynamics- University of Bergen

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Dedication

To the soul of my father, who taught me to be ambitious

and who was always emphasizing the importance of education,

To my mother, who is my role model for hard work and personal sacrifices,

and who taught me that the person who takes responsibility with persistence

can make tomorrow better than today.

To my brothers, sisters, and my family in Gaza,

To my family in Norway (my husband and my three little angles),

You were always a great motivation for me to continue working.

To Anne-Kathrin… it seems to you that you were only doing your job,

but from my perspective, you were a great example of humanity.

To all my friends in Gaza and Norway.

Life is a great blessing that we should appreciate and invest in wisely

to make it worthwhile to live for ourselves and future generations.

Amal

June 2022

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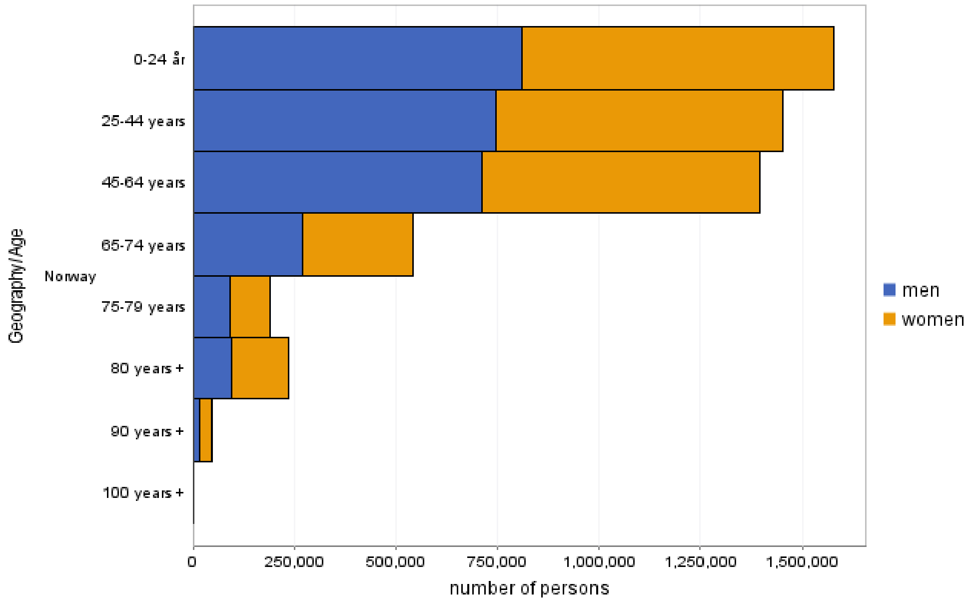
Abstract

This study uses system dynamics approach to evaluate the feasibility of reallocating policies

1 Chapter 1: Introduction

1.1 Background Information

By January 1st 2021 the total number of inhabitants in Norway was 5 391 369 (kreftregisteret.no, 2021);(ssb.no, 2021).**Error! Reference source not found.** shows the age structure by gender for the Norwegian mid-year population in 2021.



1.2.4

Figure 1:1 *Population (number and proportion) number of persons, Norway, 2021. The researcher extracted the figure from (norgeshelsa.no, 2022)*

In Norway, the underlying demographic profile reveals an ageing population structure with greater life expectancies; this results in extended periods of health-care dependency as elderly people with chronic and multiple disease conditions now live considerably longer (Lyons & Duggan, 2015). Back in 1953, when the cancer registration started in Norway, the number of inhabitants was 3 344 010(kreftregisteret.no, 2021).The population has increased by 61% from 1953 to 2021, largely because of rising life expectancy and, more recently, due to increase in net immigration. The size of the population is expected to reach 6 million in 2050, and the elderly will represent an increasing proportion of the population of Norway over the next decades (kreftregisteret.no, 2021).Recent updates from Statistics Norway estimate that the proportion of persons 70 years or older will increase from 12%, in 2020, to 21% in 2050 (ssb.no, 2021).

Cancer is a widespread disease group that affects many, either directly or indirectly as relatives(kreftregisteret.no, 2021). Before the age of 75, one in three Norwegians has been diagnosed with at least one cancer diagnosis, and in the entire population there are now almost 300,000 people with cancer in their medical history (294.855 people as of December 31 2019)(kreftregisteret.no, 2021).In addition to the demographic perspective of cancer incidents , there is the geographical perspective(Jansen, Connelly, Kelley-Gagnon, Parker, & Lipsitz, 1995). ”Norway has experienced an unexplained, steep increase in colorectal cancer incidence in the last half-century, with large differences across its counties”(Oyeyemi, Braaten, Botteri, Berstad, & Borch, 2019).

In **Figure 1:2**, we see the geographical distribution of the population in the health regions of Norway for cancer incidents in 2017[1].That gives the issue another dimension.

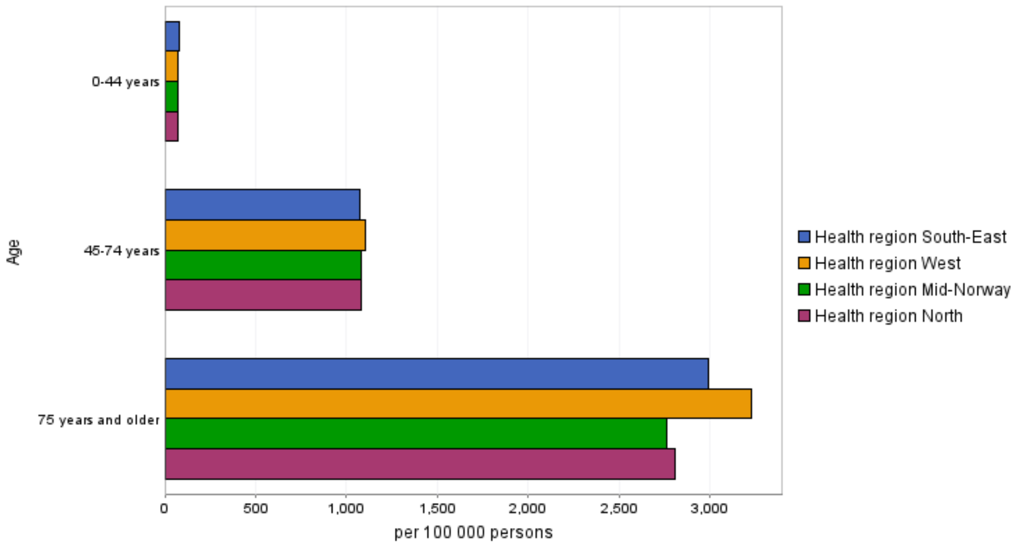


Figure 1:2 *Geographical Distribution of Cancer Incidents, All cancer types, both genders, main age groups, per 100 000 persons, 2017.The researcher extracted the figure from (norgeshelsa.no, 2022).*

1.2 Problem Formulation

“We are a growing population; we are living to an older age, and we expect more. This makes it difficult to reconcile wishes and options within the limited resources at our disposal” ("St.Meld.7 ", 2019–2020).The introduced statistics with the remarkable tendency in the demographic and geographical pattern of Norwegian population in addition to the increase of Cancer incidents between age groups (45-74) and (74+) and the fact that chronically ill cancer patients are living longer and longer will lead to increasing burdens, both for the primary and specialist health services.

[1] This is the latest year for which data is available on the database website, norgeshelsa.no.
Also, the three depicted age groups are the only groups for which the data is available, which may be because they are the most exhibited age groups for cancer incidents.

Figure 1:3 depicts the history of cancer incidents in Norway for both genders and the main age groups that the researcher found data regarding.

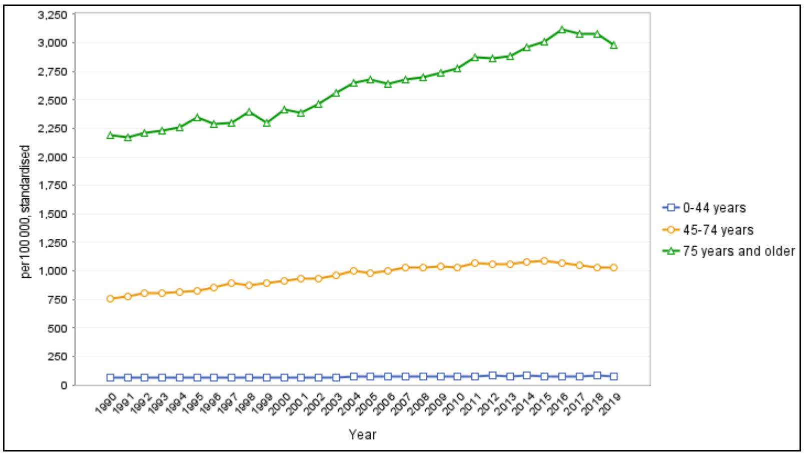


Figure 1:3 *Cancer incidents history in Norway, both genders and the main age groups. The researcher extracted the figure from (norgeshelsa.no, 2022)*

Figure 1:4 depicts the Cancer Deaths Per Year History. The general pattern shows an increase in cancer incidents and deaths, even there is a slightly decline in the last few years. "Despite the fact that more and more people are surviving, it is still the case that a significant number dies of cancer each year. More than 11.000 Norwegians died of cancer in 2019 "(kreftregisteret.no, 2021).

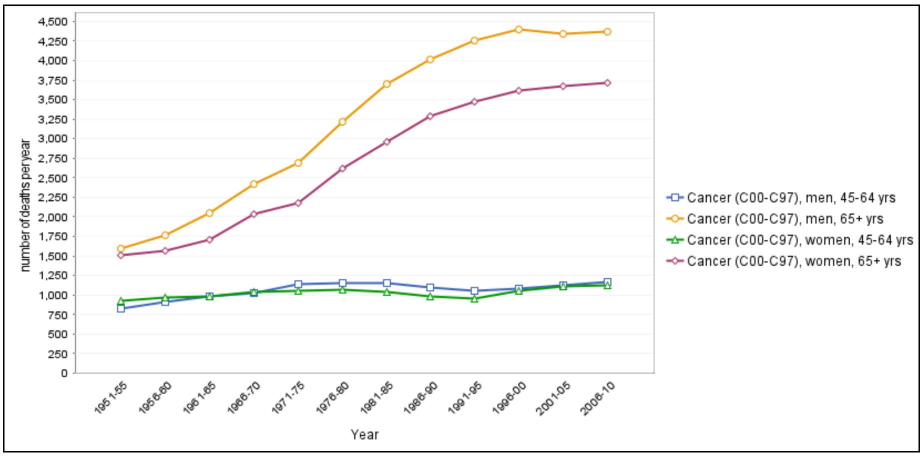


Figure 1:4*Cancer Deaths Per Year History for The Period (1951-2010)[2],All Cancer types.[3] The researcher extracted the figure from (norgeshelsa.no, 2022).*

[2] To obtain larger and more stable numbers, the Cancer Registry of Norway often present data for 5-year diagnostic periods. The use of 5- or 10-year diagnostic periods are recommended to look at statistics in small geographical areas, in age-groups with few cases or statistics relating to rare diagnoses (sb.kreftregisteret.no, 2022).

[3] C00-C97 is a cod used to indicate *Malignant neoplasms* the cancer classifications (WHO, 2022).

Through this study, the researcher explores the dynamic effects of the future increase in cancer incidents on the cancer healthcare system resilience (CHSR) in Norway. Also, to explore the effect of emergency conditions on CHSR, for example, pandemics and disease spread, as we have seen in the COVID-19 pandemic situation, The study focuses on the Norwegian population in West Norway, and age cohorts have been divided into ten age groups. The thesis presents a system dynamics model that simulates 50 years into the future. The demographic distribution of age groups shows the model's dynamic behaviors. The model includes the selected key performance indicators (KPI) for CHSR that are vital in affecting the behavior of the CHSR model.

"A resilient system is able effectively to adjust its functioning prior to, during, or following changes and disturbances, so that it can continue to perform as required after a disruption or a major mishap, and in the presence of continuous stresses"(Weick & Sutcliffe, 2015).This definition leads us to think about the challenges that constitute obstacles to achieving CHSR. In This thesis the researcher intends to consider the resources allocated for treatment as one of the factors that affect the efficiency of treatment.

In their study (Malterud, Aamland, & Fosse, 2020), they found that in Norway, general practitioners (GPs) describe unfavorable occurrences connected to duty transfer from specialists without sufficient resource allocation. Patient safety may be affected by dangerous delays, overdiagnosis, poor accountability, and probable incompetence (Malterud et al., 2020). If these delays are dangerous for patients who are waiting to be diagnosed by general practitioners, the researcher hypothesizes that such delays would be dangerous also when that relate to cancer patients, who suffer from spread of cancer cells and tumor progression. There are some studies that prove mathematically the progress of cancer cells by a nonlinear positive relationship; see for example (Quintela et al., 2017) (P.217-P.224).

1.2.1 Cancer patient pathways (CPP):

On January 1st, 2015, in Norway, cancer patient pathways (CPP) were introduced for colorectal cancer, lung cancer, breast cancer, and prostate cancer. In 2015, 28 cancer-specific pathways were established. The Norwegian Directorate of Health aimed for a well-organized and more predictable patient process without unnecessary non-medical delays related to assessment, diagnosis, treatment, and/or rehabilitation (Møller, 2021).

The number of days that each stage of the medical investigation should take has been defined for each pathway (Helsenorge.no, 2020). Phase 1: The period between receiving the patient referral in the hospital and when the patient attends his first investigation appointment.
80% of all cancer patients should start treatment within 20 working days that the referral has been received (Ministry-of-Health, 2013) .Phase 2: The time between patient's attending his first investigation appointment and the completion of his investigations, surgical treatment, and chemotherapy “Treatment Process “. Phase 3: The time between the patient's surgical treatment and completing palliative control “Following-Up process”.

The cancer patient pathway in Norway depends mainly on the resources that the ministry of health has allocated for it. Regarding (Vistad, Bjørge, & Skeie-Jensen, 2020), there is a need for change in cancer follow-up. The COVID-19 pandemic highlights the need to consider alternative ways to follow up cancer patients. "Letting patients systematically report any symptoms electronically (electronic patient reported outcomes, ePRO) during and after a completed course of cancer therapy has shown promising results in two randomized studies"(Vistad, Bjørge, & Skeie-Jensen, 2020).Considering these results from an administrative perspective, shows that following-Up phase of treatment is more flexible and can be managed remotely (Muller & Berg, 2020; Wagner, Austin, Davis, Hindmarsh, & et al., 2001).

The treatment stage, in contrast to the follow-up phase, necessitates several admissions from the patient and is difficult to do remotely, such as surgical treatments, blood tests, and chemotherapy (A. Miller, Hoogstraten, Staquet, & Winkler, 1981; K. D. Miller et al., 2019). Even there is a difference between these two stages, we see that the health system in cancer treatment allocates the resources without taking into consideration this fundamental approach (Vistad et al., 2020). In the long run, there is an increase in demand for resources to be allocated to treatment, and that increases the pressure on the health system. That pressure would also increase the delay in treating patients that should be prioritized. Also, that would have a negative effect on life quality for cancer patients. For example, a six-month delay in cancer surgery is expected to result in a loss of 18.1 to 15.9 life-years gained(Bailey, Black, & Swanton, 2020; Sud et al., 2020).

In their study (Bordonaro et al., 2012),the results show that Specialists in charge of the service reported that nursing personnel had outstanding control over the procedure, with only a few medical visits. This type of active home care increases quality of life and oral treatment adherence

(Bordonaro et al., 2012). The number of missed hours of work for caregivers has been reduced as a result. These results indicates that cancer health sector can have less pressure by decreasing the pressure on treatment resources by adapting remote patient monitoring (RPM) in following-Up patients.

1.2.2 Remote Patient Monitoring (RPM)

Given the rising prevalence of Cancer incidents in the Norwegian population, as well as the rising use of unnecessary specialist health services, it is unrealistic to expect specialist health care providers to be able to provide the type of frequent, preventative, and non-acute monitoring that many patients would benefit from (Muller & Berg, 2020). The Norwegian Ministry of Health has established a unique definition of Remote patient monitoring (RPM) that identifies the processes at which data is sent remotely from a non-institutionalized patient to a physician, who either manually examines the data and contacts the patient, or the data is automatically analyzed (by the device), but clinicians are called for follow-up if results are alarming. The goal is to reduce needless and avoidable specialized use (Muller & Berg, 2020).

"Unnecessary check-ups cause many cancer patients to be anxious about a recurrence that is unlikely to occur. This makes for crowded outpatient lists and greater difficulties in prioritizing the right patients for follow-up " (Vistad et al., 2020). According to a recent study (Koinberg, Engholm, Genell, & Holmberg, 2009) , more thorough follow-up does not improve medical safety. Despite the overall number of resources spent, there are signs that numerous other ways may be employed (Koinberg et al., 2009). Despite the large overall number of resources spent on follow-up programs and signs that numerous other ways may be employed effectively, there is no systematic discussion regarding follow-up program expenses and/or cost-effectiveness. Furthermore, there are evidence that high-quality programs may be implemented with the help of skilled nurses (Koinberg et al., 2009).

From this perspective, the researcher aims to use the system dynamics approach to analyze the results of considering the resources management reallocation in the treatment process and following-up process of patients, hence achieving CHSR.

1.2.3 Problem Boundaries

The introduced problem gives the reader many indications about the CHSR in Norway. It seems that CPP is a helpful procedure that can mitigate patients' suffering. On the other hand, decision makers need to think about the resources that are used and how they can increase their efficiency through rational resource allocation. In this study, the region west of Norway is used as the research boundary. The reason of Using the region west of Norway rather than just one city is that the data found is organized by health regions rather than cities. The other reason is that there is only one public hospital in Bergen that provides cancer treatment for the whole population in the west region of Norway. That could also cause some challenges for patients who travel from different counties to Bergen to get treatment. Including the geographical dimension to the CHSR model could make it more complicated, and the researcher did not find sufficient data that could be used to add the geographical dimension to the model.

1.2.4 Problem Summary

Due to the demographic aging of the population and the increase in life expectancy, there is an increase in the number of cancer incidents and deaths in Norway, and the pressure on hospitals can be expected to increase. Which policies can be suggested to alleviate these pressures and increase CHSR in the health sector? Can reallocation of treatment and following resources help in increasing the efficiency of cancer patient treatment, or in other words, increase the CHSR in the health sector?

To avert a downstream public health disaster of needless cancer deaths, cancer diagnostic and surgical routes must be maintained at normal throughput, with fast care to any backlog that has already built, according to (Sud et al., 2020) .From that point of view, Can reallocation of treatment and following resources help in increasing the CHSR in the health sector, by other words, can reallocation of resources build a system that is able to perform as required during disturbances or shocks in that system?.

Regarding to Nielsen et al. (2020a), Norway has a free, national health care system that should be equally available to every citizen, regardless of personal characteristics, social status, and area of residence. However, data published by the Norwegian Directorate of Health has shown substantial geographical variation in the proportion of cancer patients being referred to a CPP (Nilssen et al., 2020b). Could this variation become narrower by introducing some policies that make cancer patient pathways CPP resilient?

1.3 Research Objectives

1.3.1 The researcher aims by conducting this thesis to understand the dynamic interactions between Cancer treatment system in West Norway and cancer patients demand for treatment for 50 years in the future.

1.3.2 To understand the difference between treatment and following-up process, and how can resources allocation affect the efficiency of each of them, hence affecting CHSR.

1.3.3 To understand the dynamics of population age groups and find out which age groups that have more demand on cancer treatment in the future.

1.3.4 The purpose of this model is to provide decision makers by insights for policies that increase their awareness to the rationality of resource management allocation and to test different policy scenarios that can be simulated to predict the behavior of the key performance indicators of CHSR Model. That helps decision makers to understand the impact of treatment efficiency to achieve CHSR.

1.4 Research Questions

1.4.1 What is the difference between treatment and following-up process, and how can resources allocation affect the efficiency of each of them, hence affecting CHSR in health sector?

1.4.2 What is meant by resilience in health sector, and what are the benefits of adapting that for health sectors and patients, namely cancer patients?

1.4.3 How can system dynamics approach help in achieving CHSR?

1.4.4 What are the main dynamic interactions that are included in the system dynamic structure for Cancer treatment system in West Norway?

1.4.5 What policy options can be identified to achieve CHSR in health sector in West Norway and what are their dynamic implications?

1.4.6 What are the key performance indicators that we should take into consideration when we evaluate the efficiency of policy adapted to achieve CHSR?

1.4.7 which age groups that have more demand on cancer treatment in the future? And how can resource allocation management fulfill their demand?

1.5 Hypothesis

1.5.1 Dynamic Hypothesis

The problem discussed in this research reveals that there are many dynamic dimensions that interact with each other. The CHSR model designed to simulate this problem indicates that there are many feedback loops that interact and cause the key performance indicators to behave. These feedback loops can be represented by a causal diagram that is made up of variables linked by arrows that represent the causal influences between variables. The two-lined arrows represent various delays between two connected variables. To reflect how the dependent variable changes as the independent variable changes, each causal relationship is assigned a polarity, either positive (+) or negative (-). It is worth noting that the loop identifier circulates in the same direction as the loop it relates to

Population dynamics are the main dynamics in this model because that shows us to what extent there is a demand for cancer treatment in West Norway. **Figure 1:5** shows the balancing and reinforcing loops that result from interactions between population dynamics and cancer patients. **Deaths Balancing loop B0:** illustrates that more population will cause more deaths, and then more deaths will cause a decrease in total population.

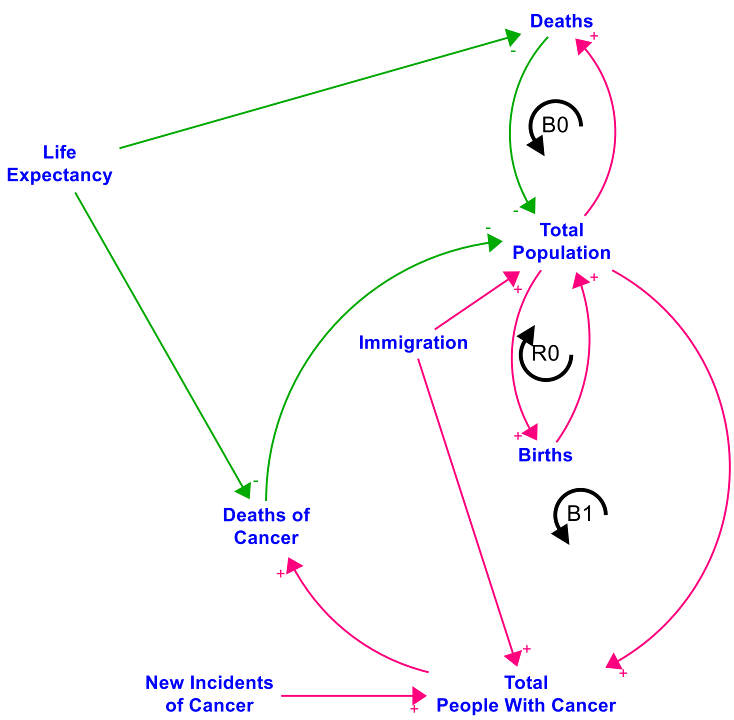


Figure 1:5 *CLD For Population dynamics and Population with Cancer Dynamics.*

Cancer Patients are part of Population, so in the **Population Dynamics and Cancer Patients Balancing Loop B1,** the more growing population cause more probability of new cases of cancer. As most of cancer types and incidents are discovered in older age groups. When total population increases, that leads to increase in total Population with cancer, then there will be more deaths of cancer and that causes a decrease in total population. The researcher assumes life expectancy is an exogenous factor that causes a decrease in both deaths and subsequently, deaths of cancer. **Births reinforcing loop R0,** shows that the increase in population will cause more births, and then more births will cause an increase in total population. Immigration is considered by the researcher as an exogenous factor. More immigrants will cause an increase in the total population, causing an increase in total people with cancer.

As it is introduced in the problem formulation, cancer patients go through three phases. In the CHSR Model, we represented the main phases, which are: the second "Treatment Process" and the third phase "Following-Up Process". As this model is considering the reallocation of resources, the main resources that are considered in this model are only specialized doctors and nurses. Contrary to machines and chemotherapy devices, human resources can be easily and flexibly reallocated.

When the total resource fraction equals one, the resources allocated on the treatment process equal one minus the resources allocated to the follow-up process. That means, allocating more resources to one part of the equation causes a decrease in the other, that relationship is represented by **the resource's allocation reinforcing Loop R3** that is shown in ***Figure 1:6***

As it is explained in the introduction, in CPP, the pressure on the health system equals the pressure on treatment resources divided by the pressure on following-up resources.

That equation indicates that we can get less pressure on the cancer healthcare system by decreasing the pressure on treatment resources and increasing the pressure on follow-up resources.

As it is explained in the problem statement, the researcher hypothesizes that reallocating the resources can increase the efficiency of treatment and stimulate the system to work efficiently under shocks, hence affecting cancer treatment resilience positively. ***Figure 2:2*** depicts the resulted **Resilience Balancing Loop B2**. This is a fundamental loop that balances follow-up resources and treatment resources by reducing pressure on the entire cancer healthcare system through rational allocation. The increase in total people with cancer will cause more deaths of cancer, then more deaths of cancer cause a decrease in recovered people. When there are more recovered people, that will decrease the pressure on treatment resources. The more pressure on treatment resources causes more pressure on the whole cancer healthcare system. Then when there is more pressure on cancer healthcare system, there will be less resources allocated to the follow-up process. That increase will mean that there will be less resources allocated to the treatment process. When there is an increase in resources allocated to the treatment process, that will increase the treatment rate. When the treatment rate increases, there will be more people who are treated and need only follow-up. That increase causes another increase in the number of people with cancer. And deaths of cancer.

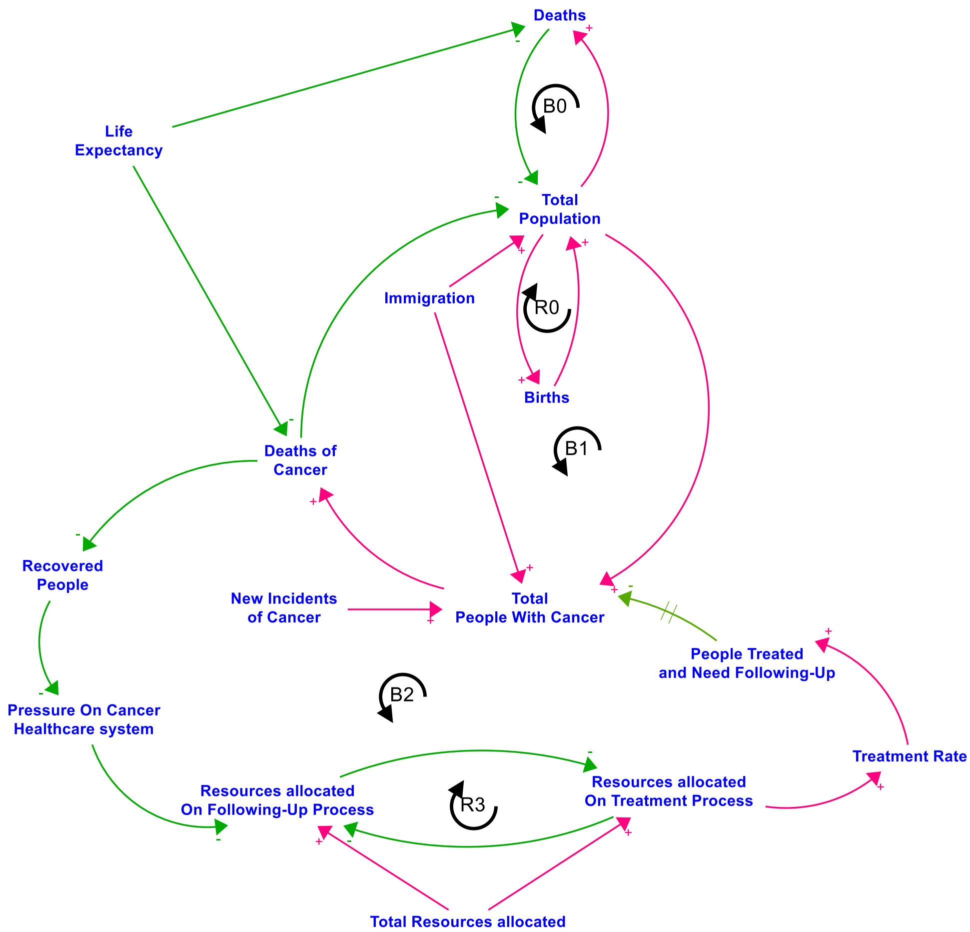


Figure 1:6 CLD of Dynamic Hypothesis after adding B2 and R3 to the population with Cancer dynamics

The balancing loop B2 dominates many loops in the system. That is discussed in Chapter 5 under the subtitle "feedback analysis." That feedback analysis is revealed after presenting the model structure that is introduced in chapter 5.

1.6 Major Hypothesis

1.6.1 Reallocating treatment resources will relieve pressure on hospitals and increasing health Care system resilience.

1.6.2 Allocating more resources on treatment phase of patient medication will relieve pressure on the hospitals and increase cancer healthcare system resilience.

1.6.3 Allocating less resources on following-up phase of patient medication will relieve pressure on hospitals and increase cancer healthcare system resilience.

1.6.4 Following-Up phase of treatment is flexible and many of monitoring tasks can be conducted remotely

1.6.5 Reallocating treatment resources will relieve pressure on hospitals and thereby increase cancer healthcare system resilience, but maybe also will introduce new challenges.

2 Chapter 2: Methodology

2.1 Research Strategy and methodology Choice

A mixed-method research technique is used in this thesis. In mixed-methods technique, the researcher uses both quantitative and qualitative approaches (Denscombe, 2012; Lane, 1999; Snyder, 2019). As (Heshmat & Eltawil, 2018) pointed out, cancer therapy is a complicated system with many interconnected elements, a mixed-method research technique is appropriate to achieve the objectives of this thesis: namely to understand the dynamic interactions between Cancer treatment system in West Norway and cancer patients demand for treatment and to understand the difference between treatment and following-up process, and how can resources allocation affect the efficiency of each of them, hence affecting CHSR. Simulating these interrelated parts of cancer healthcare system over time in a model that mimics the real behavior can be useful to understand such interrelations.

The qualitative phases to be applied in this study include conceptualization and model formulation, which follow the system dynamics modeling presented in the SD literature (Luna-Reyes & Andersen, 2003) . These phases are useful to get insights about the complex dynamics between population dynamics, cancer medication demand, and the health sector's ability to fulfill that through treatment and follow-up phases as described in the theoretical frameworks. A thorough literature review (Bordonaro et al., 2012; Hall & Lloyd, 2008; Heshmat & Eltawil, 2018; Vistad et al., 2020) of cancer therapy theoretical research was undertaken during the qualitative stage. The data was then gathered through a systematic literature study, and qualitative SD methods were utilized to graphically portray the concepts discovered in the literature. Stock and flow diagrams, as well as casual loop diagrams, were used to develop the model formulation.

As a result, the qualitative study's stock and flow diagrams, as well as causal loop diagrams, were proceeded in a quantitative model after modeling phases of model validation and behavior analysis, which provided simulation results to prove the internal consistency of the theories and ensure that behavior can be generated by its underlying assumptions (Repenning, 2002).

2.2 Data Collection and analysis

Following (Snyder, 2019) principles for evaluating the quality of a literature review, The literature review offered in Chapter 4 of this thesis seeks to address the most important components of existing analytical studies of cancer treatment resilience and resource reallocation to achieve CHSR. There is no system dynamics literature on reallocating resources to achieve CHSR in West Norway. Then as a result, the literature used in this study is gathered from a variety of related and relevant studies that offered studies on the effectivity of reallocating resources in healthcare sectors. In addition to studies pertinent to the Norwegian cancer healthcare system.

3 Chapter 3: Literature Review

This chapter includes a review of the literature that relates to the research project to find out answers to the first and second research questions. There is not any research that has been conducted to explore the effect of reallocating resources in Cancer healthcare system resilience in west Norway using a system dynamic approach, but there are many global studies that discussed generally building a resilient healthcare system using system dynamics approach, without considering a specific disease, also there are some studies that explored the effect of crises in health care systems.
The researcher gets some knowledge from the literature review about each concept related to this thesis, and that knowledge would be used to clarify some concepts that related to cancer healthcare system resilience in West Norway and that knowledge helps to build a structural model that is used to suggest policies and recommendations.

3.1 Efficiency and Resilience in Health care systems:

To get better understanding about the relation between cancer treatment efficiency and resilience in health sectors, definitions for these concepts are needed to explain the assumptions and knowledge considering the explanations provided in this concepts' definitions.

Regarding to the Australian Productivity commission, (Productivity-Commission, 2015)“Efficiency involves the allocation of available resource inputs in a way that provides the best outcomes for the community”.

Quantifying and measuring efficiency in the health sector is a challengeable approach (Aktaş, Ülengin, & Önsel Şahin, 2007; Jacobs, Smith, & Street, 2006; Peacock, Chan, Mangolini, & Johansen, 2001) because of its complexity. The policymaker's definition of efficiency is the amount to which objectives are met in relation to the resources utilized. There may also be some consideration of external conditions that impact the system's capacity to attain its goals (Jacobs et al., 2006).

Depending on the methods represented by (Jacobs et al., 2006; Peacock et al., 2001) , this thesis adopts mainly five measures of efficiency, which are: **increasing the number of treated people , decreasing the number of total population with cancer, decreasing deaths of cancer, and increasing recovered people, and decreasing pressure on cancer healthcare system**. To confirm the feasibility of efficiency, these measures will be tested in the case of shocks or crises. Such tests evaluate the feasibility of resource reallocation during emergency conditions, hence, to test systems resilience. System resilience is a developing topic in health system research, and definitions of it differ from the previous research (Fridell, Edwin, von Schreeb, & Saulnier, 2020) . Resilience emphasizes the functions required by health systems to respond to and adapt to health shocks, introducing a dynamic dimension into more static health system models that can assist the system in dealing with surges in demand and adapting to changing epidemiology and population expectations of care (Margaret E. Kruk et al., 2017).

The notion brings valuable new ideas from other areas to health-care systems. Resilience is based on complex systems concepts that have been identified as significant in health systems but are seldom implemented, such as the connectivity of health and non-health actors and the relevance of feedback loops (De Savigny & Adam, 2009; Margaret E Kruk, Myers, Varpilah, & Dahn, 2015; Margaret E. Kruk et al., 2017; Narwal & Jain, 2021).

The resilience in healthcare research program is exploring resilience as a multi-level phenomenon and considers adaptive capacity to change as a foundation for high quality care (Wiig et al., 2020). (Wiig et al., 2020), therefore, define healthcare resilience as: the capacity to adapt to challenges and changes at different system levels, to maintain high quality care.

Resilience within a health system, a definition: “A health system’s ability to absorb, adapt to, learn and recover from crisis born of short term shocks and accumulated stresses, in order to minimize their negative impact on population health and disruption caused to health services.”(new-reality-blog.com, 2021). This concept brings us to the fundamental goal of this research, which is to create a resilient cancer healthcare system.. Every day, societies face new problems, particularly in healthcare systems and cancer-prevention approaches. To be able to handle these issues, decision-makers must be prepared, as we saw during the COVID-19 epidemic. Such planning and preparation strengthen .

By combining these definitions and applying that on cancer treatment system, we get a theoretical conceptualization of the vital role of efficiency and early planning to achieve resilience in cancer health care system.

3.2 Cancer Treatment in system dynamics modeling.

Cancer usually is cured systematically by surgery, radiotherapy, and chemotherapy (Heshmat & Eltawil, 2016). In their paper (Heshmat & Eltawil, 2016),the researchers created a general system dynamics model in their paper that clarifies the various factors influencing treatment plans such as the number of cancerous cells, drug accumulation, and toxicity (Williams et al., 1967). Their model (Heshmat & Eltawil, 2016) depicts that with repeated chemotherapy doses, the simulation results showed a decreasing trend in the number of cancerous cells over time. The results show that the model is more sensitive to dose cancellation than dose delay, implying that canceling doses is more dangerous to the patient's health than delaying doses. In their paper (Heshmat & Eltawil, 2018), they presented a system dynamics model to investigate the efficacy of chemotherapy treatment plans. They proposed variables such as the impairment caused by tumor growth as well as the adverse effect of chemotherapy doses, as well as treatment efficacy, which is the response obtained by following a chemotherapy protocol. The researchers' findings show that the number of cancerous cells and toxicity levels decrease over time in a reasonable manner. They tested the model on a real chemotherapy protocol for lymphoma, and the proposed model fit the protocol well. The findings indicate that dose cancellation and delay have a negative impact on treatment efficiency.

3.3 Remote cancer follow-Up/ Home-Based treatment

The notion of cancer patients receiving treatment at home is not new. At their study, (Wagner et al., 2001), the researcher highlighted that high-quality chronic disease care is defined by constructive interactions between the practice team and patients that regularly offer the evaluations, self-management assistance, therapy optimization, and follow-up that are linked with positive results. Face-to-face meetings are not required for these exchanges. The efficiency of utilizing a computer or phone for this purpose is well documented (Wagner et al., 2001).

Several early research investigated the viability of treating patients at home (Wardley et al., 2021) , Such studies evaluated the efficiency and feasibility of following-Up patients remotely ,see for example: (Annals-of-Internal-Medicine, 2005; Hall & Lloyd, 2008; Mooney et al., 2020; Rischin et al., 2000; Shepperd et al., 2009). In addition to the studies discussed the efficiency of home-treatment, there are also some studies that depicts cost analysis of that type of treatment , see for example (Cryer, Shannon, Van Amsterdam, & Leff, 2012; Rischin et al., 2000) .

The advent of oral chemotherapy represents a real benefit for patients, especially in terms of quality of life (Bordonaro et al., 2012). Home-based cancer treatment represents a new model of care that can include active assistance of patients treated with oral, subcutaneous, and even intravenous agents (chemotherapy or biologics). The Active Home Care project has significantly reduced the number of hospital visits made by patients and their companions , resulting in a reduction in hospital costs (Bordonaro et al., 2012).

Patient-centered home care can be combined with more typical hospital-centered care, particularly in groups of educated and trained patients (Tralongo et al., 2011).According to a UK analysis of 'care in the home,' the benefits of treating patients (including cancer patients) at home include improved adherence, quality of life, patient activation, and financial savings (Wardley et al., 2021). Another study (Hibbard & Greene, 2013) , conducted that policies and treatments targeted at enhancing patients' roles in controlling their health care may and should contribute to better results, and patient activation can and should be quantified as an intermediate outcome of care associated to better outcomes.

Considering these studies that shows the flexibility and efficiency of home treatment, also considering CPP that provided in chapter one, this thesis considers that following-Up phase of cancer treatment causes less pressure on cancer healthcare system in contrast to treatment phase of cancer medication.

3.4 Reallocating resources effect in cancer healthcare System resilience

There are not any research that has been conducted to explore the effect of reallocating resources in Cancer healthcare system resilience in west Norway using a system dynamic approach, but there are some global studies that discussed generally building a resilient healthcare system using system dynamics approach, without considering a specific disease healthcare system, see for example (Chow, Loosemore, & McDonnell, 2012; Pishnamazzadeh, Sepehri, & Ostadi, 2020). One study considered some factors that affect the system resilience negatively, like weather conditions (Chow et al., 2012). Another study considered four key performance indicators (KPI) of hospitals, which are: patient satisfaction, patient waiting time, staff burnout, and staff satisfaction. In their study (Pishnamazzadeh et al., 2020), a system dynamics approach was used to investigate the effect of disruptions on the four KPIs, and multiple scenarios were developed to assess the toleration of the hospital KPIs. The study determined that disruptions alter the external variables. As a result, hospital administrators should develop certain ways to prevent them, such as staff-related aspects.

Also there are some global studies that narrowed the scope to reveal the impact of crises on cancer treatment, but they used theoretical approaches rather than system dynamics approach , see for example (Rubio-San-Simón et al., 2020; Sud et al., 2020).Both studies concluded that the challenges reported had an impact on both patient treatment and monitoring activity. Efforts should be made to reallocate resources to minimize missed chances for patients. Given these results from both studies (Rubio-San-Simón et al., 2020; Sud et al., 2020), this thesis aims to narrow the scope into cancer healthcare system resilience by exploring the feasibility of reallocating resources on treatment phase and reducing these resources allocated on following-Up phase.

(Wolstenholme et al., 2007) in their study of reallocating mental health resources, they mentioned the notion of reallocating resources, by emphasizing that the effectiveness of the entire system will be substantially enhanced if we can acquire the "right talents, in the right location, at the right time"; provision will thus be really needs led rather than provider led (Wolstenholme et al., 2007) . But there is no research that has been conducted to study the effect of reallocating resources on cancer healthcare system resilience. Therefore, this study has been conducted.

System dynamics approach has been applied in many aspects that is related to health care planning, see for example (Lin et al., 2021; Trellevik, 2008) . Such studies utilized approaches for predictions of demand in healthcare sectors and labor market for health personnel to inform strategic workforce planning, improve nursing training, and strategically redeploy financial resources toward hiring more people. In contrast to mentioned studies (Lin et al., 2021; Trellevik, 2008) , this thesis focuses on cancer healthcare planning by considering reallocating the current resources in the healthcare system, that is assumed to initiate CHSR .

3.5 Literature Review Summary

As it discussed in the literature review, there are many variables that interacts in the CHSR model, and there are some concepts that are used in the conceptualization of this model. Therefore, the researcher Summarized these interactions and concepts in **Table 1**

Table 1 Related concepts and relationships found in the literature of building CHSR through resources management reallocation

Concept/Relationship	Definition/Explanation	Source
Efficiency	Efficiency involves the allocation of available resource inputs in a way that provides the best outcomes for the community	(Productivity-Commission, 2015)
Healthcare system Resilience	The ability of the health systems to prepare for and effectively respond to health crises while maintaining its core functions when a crisis hits, and to reorganize (adapt and transform) if conditions require it, based on lessons learnt during the crisis	(Margaret E Kruk et al., 2015; Margaret E. Kruk et al., 2017; Narwal & Jain, 2021).
Measures of efficiency in healthcare systems	-Delay time in patients' treatment -The number of treated people -The number of total populations with cancer.	(Jacobs et al., 2006; Peacock et al., 2001)
The relationship between home-based treatment and efficiency of treatment.	Positive relationship between home-based treatment and efficiency of treatment.	(Annals-of-Internal-Medicine, 2005; Hall & Lloyd, 2008; Mooney et al., 2020; Rischin et al., 2000; Shepperd et al., 2009; Wagner et al., 2001; Wardley et al., 2021)
Cost analysis of remote treatment or remote following-up patients	The Active Home Care project has significantly reduced the number of hospital visits made by patients and their companions, resulting in a reduction in hospital costs	(Cryer et al., 2012; Rischin et al., 2000)

Contribution of Patients in treatment process.	Positive results when policies and treatments targeted at enhancing patients' roles in controlling their health care	(Hibbard & Greene, 2013)
The effect of delays on treatment efficiency.	Dose cancellation and delay have a negative impact on treatment efficiency.	(Heshmat & Eltawil, 2016, 2018; Williams et al., 1967)
The impact of crises on cancer treatment	Negative impact on both patient treatment and monitoring activity	(Rubio-San-Simón et al., 2020; Sud et al., 2020)
Relationship between reallocating resources and the effectiveness of the entire healthcare system	Positive relationship between reallocating resources and the effectiveness of the entire healthcare system. The effectiveness of the entire system will be substantially enhanced if we can acquire the "right talents, in the right location, at the right time"	(Wolstenholme et al., 2007)

4 Chapter 4: Model Description

To study the dynamics described in the literature review of cancer healthcare system resilience, the researcher built a system dynamics model.

4.1 Model Overview

As mentioned in the hypothesis section, this model focuses on the dynamics of the supply and demand interactions within cancer treatment in west Norway. The aim of simulating this model is to help decision makers find the best policies and strategies that lead to CHSR

"Small system dynamics models are unique in their ability to capture important and often counterintuitive insights relating behavior to the feedback structure of the system without sacrificing the ability for policymakers to easily understand and communicate those insight" (Ghaffarzadegan, Lyneis, & Richardson, 2011) .From this perspective, the researcher aimed to simplify the idea of this project and to concentrate on the variables that helps decision makers to utilize this model.

The model captures the population dynamics in west Norway, and the behavior of population age groups that suffer from cancer disease. As mentioned in problem statement, alder age groups are exposed to get cancer more than younger age groups. As Norwegian population have high life expectancy, that increases the load on health sectors to be able to offer treatment and care because alder people demand more care than other age groups. This conceptualization of this part of model is modeled in *Population Dynamics Sector*.To get better understanding of cancer treatment system in Norway, the researcher modeled *Cancer Treatment Process Sector*, which represents the stages that patients go through when they start treatment then get recovered.

From an administrative perspective, the researcher focuses on resources management allocation to discover how can decision makers distribute health personnel between patients efficiently, to get the best performance, therefore the researcher modeled the *Resources Management Sector*.

4.2 Model Structure:

To get a comprehensive understanding of the Cancer treatment Resilience Model, the reader needs to understand the qualitative and quantitative aspects of it. Qualitative aspect can be reached by the variables casual loop linking, while quantitative aspect can be reached through the equations formulated for theses variables that are structured in the form of stocks and flows and auxiliary variables. In Appendix C, there is a detailed explanation for the model variables, equations, units, and the resources that the researcher referred to them when she conceptualized the relationships between variables.

4.2.1 Population Dynamics Sector.

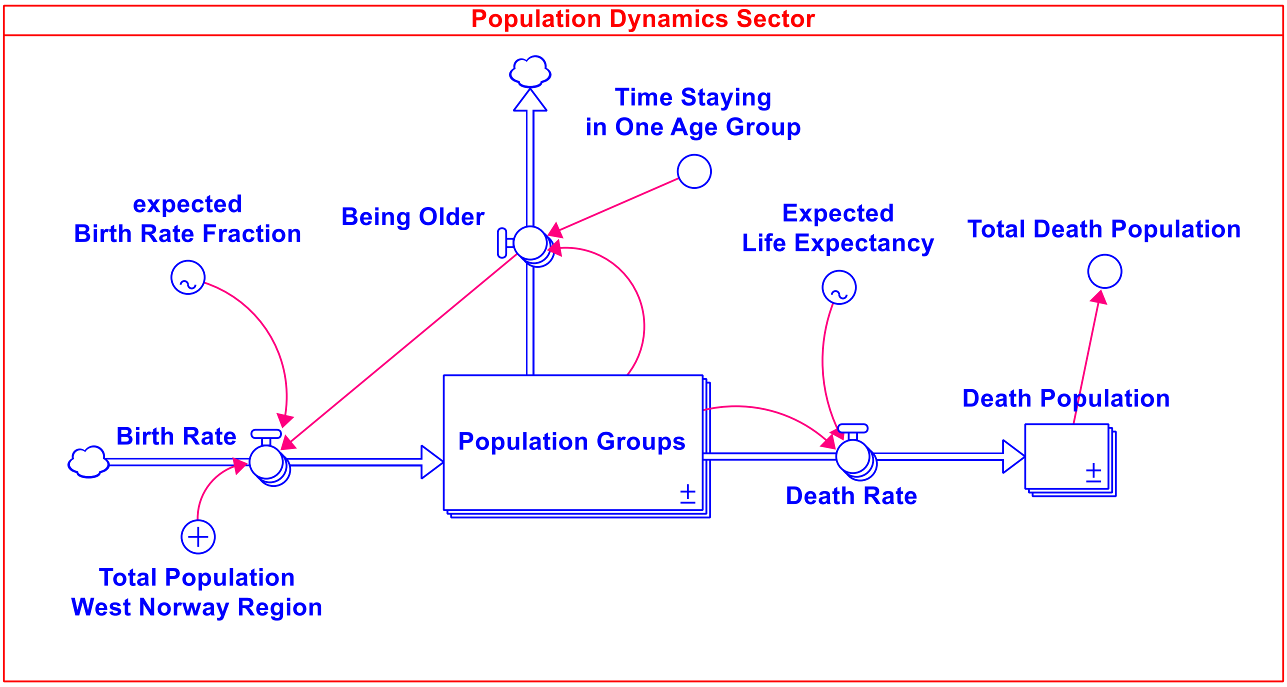


Figure 4:1 Population Dynamics Sector.

4.2.2 Cancer Treatment Process Sector

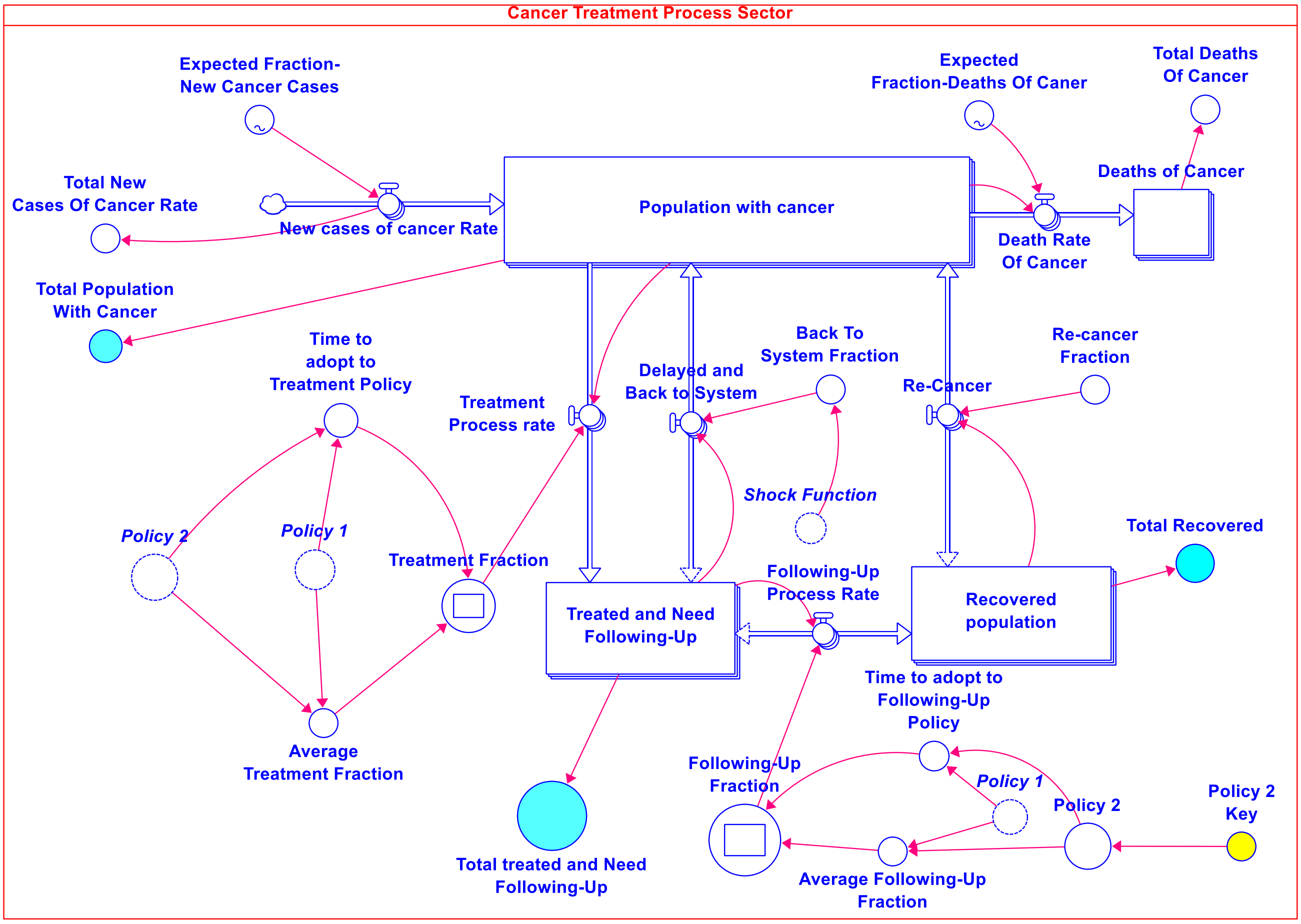


Figure 4:2 Cancer Treatment Process Sector

4.2.3 Resources Management Sector.

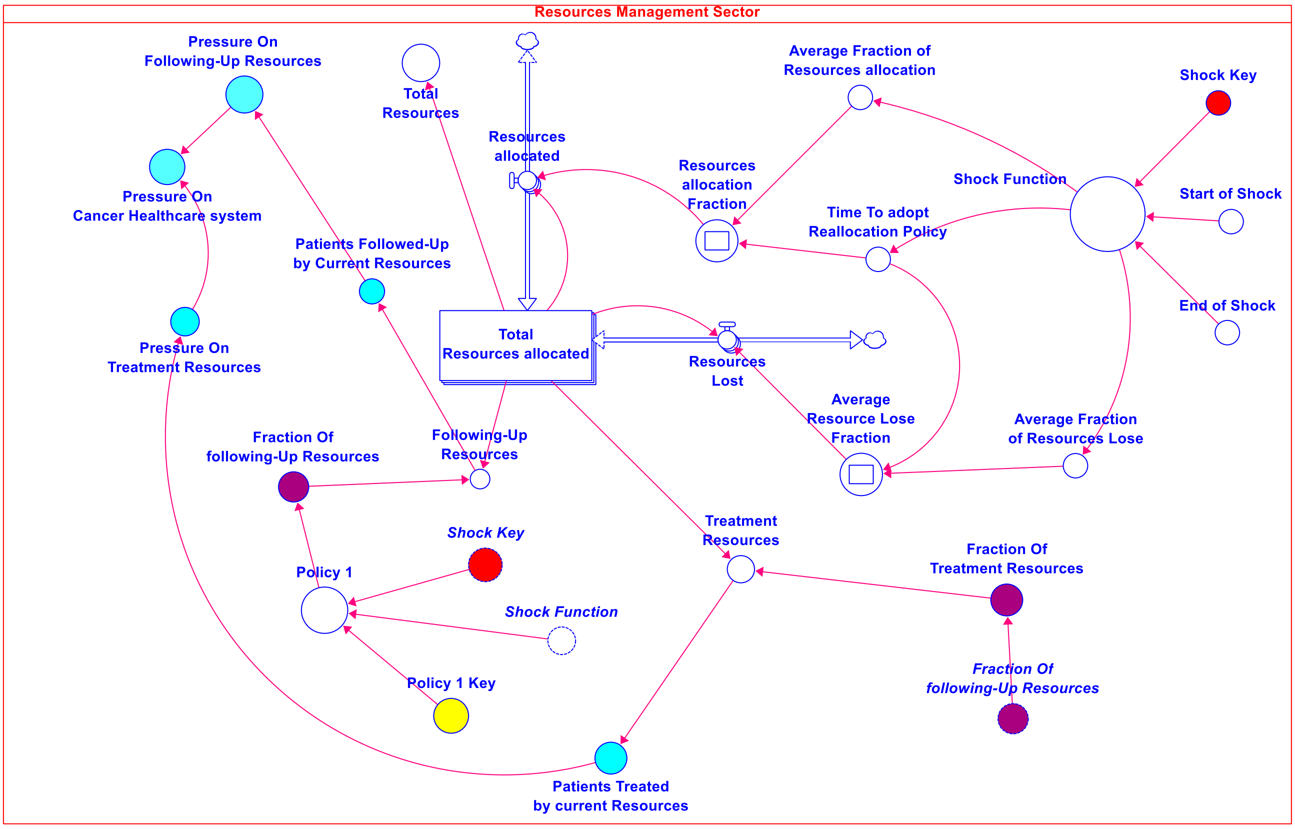


Figure 4:3 Resources Management Sector

4.3 Feedback analysis

Feedback is a basic notion in System Dynamics. However, because humans have cognitive capacity constraints, mental models frequently fail to contain the important feedbacks driving system dynamics (Forrester, 1992; Vennix, 1996)

This chapter offers a broad overview of the model's primary feedback loops. According to (Richardson & Pugh III, 1981), feedback is "a closed sequence of causes and consequences, that is, a closed line of action and knowledge". All dynamics are caused by the interplay of two types of feedback loops: reinforcing loops (R), which reinforce whatever is going on in the system, and balancing loops (B), which negate or oppose changes.

As per the dynamic hypothesis discussed in chapter 2, there are nine loops in the CTR model. Four of them are reinforcing loops, while the other five are balancing loops. B2 is dominating the system. It includes the loops R1, R2, R3, B3, B4. This chapter focuses on these loops and how they interact to cause resilience in the system. ***Figure 4:4*** Depicts the main Loops that are dominated by loop B2 which shows the resilience in system.

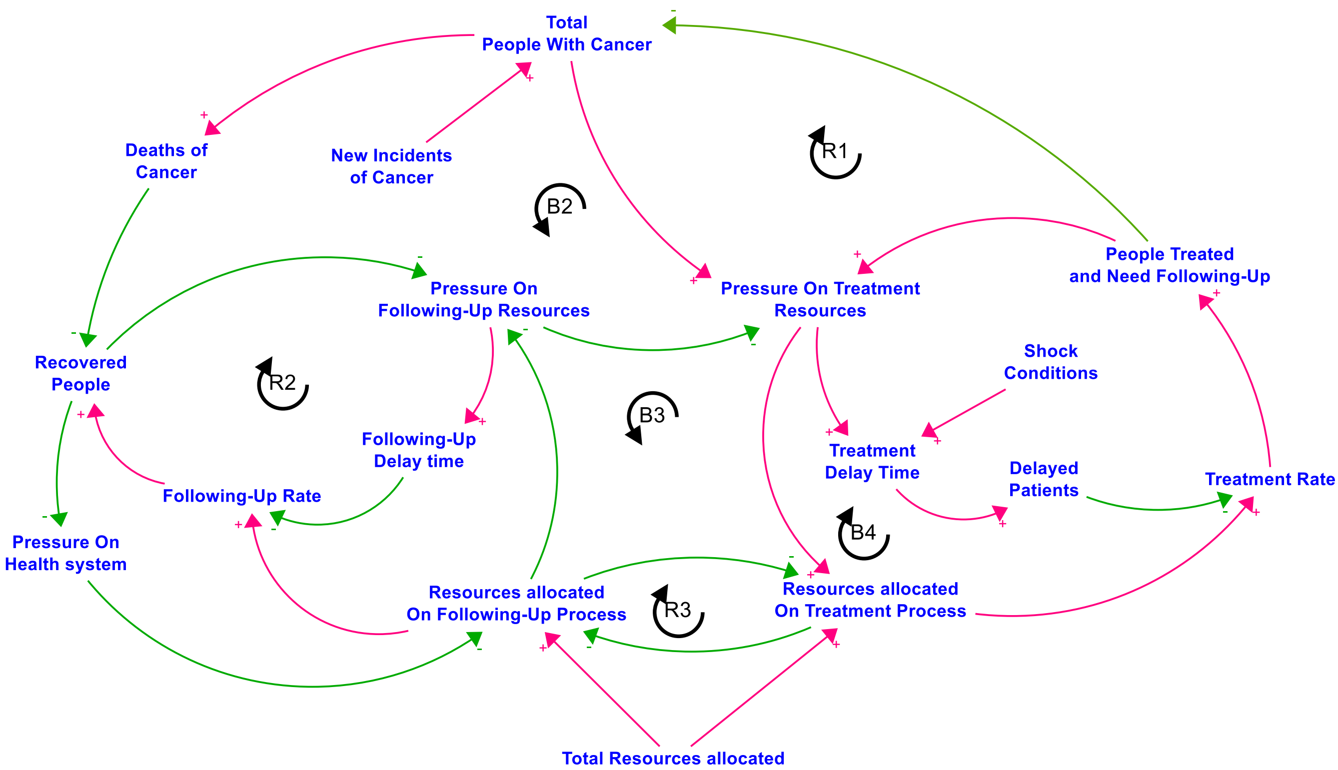


Figure 4:4 Main loops Dominated by Loop B2

R1: Treatment Delay Reinforcing Loop:

Increase in the number of people with cancers will cause pressure on Treatment Resources. that increase in pressure will cause increase in Treatment Delay Time, then the number of delayed patients will also increase. That increase in Delay will cause less treatment rate. When treatment rate increases, there will be more people who are treated and need only following Up, that means there will be less gap in Utilization of treatment resources. If this gap increase, there will be again more increase in the number of people with cancer.

B4: Resource allocation and Treatment Resources Utilization Balancing Loop:

The Increase in the number of people with cancers will cause pressure on Treatment Resources. that increase in pressure will cause increase in resources allocated on Treatment process, then that will cause increase in treatment rate. When treatment rate increases, there will be more people who are treated and need only following-Up, that means there will be less gap in Utilization of treatment resources. If this gap increase, there will be again more increase in the number of people with cancer.

R2: "Following-Up Delay Reinforcing Loop"

That includes an increase in following-Up Rate and that causes and increase in Recovered People, that increase causes less gap in Utilization of following-Up resources. When this gap increases, there will be more pressure on following-up resources. Then when there is more pressure on following-up resources, that will increase delay time in control and following-Up process, then there will be a decrease in the following-up rate again.

B3: "Resources allocation Management Balancing Loop" This is a fundamental loop which includes the allocation management of resources. when there are more resources allocated on treatment process, that will cause a decline in the resources allocated on following-Up process, and then when there is an increase in resources allocated on following-up process, that will cause a decline in Pressure om Following-Up resources. The increase in Pressure on Following-Up resources will case more less pressure on Treatment Resources.

R3: "Resources Allocation Reinforcing Loop"

When there are more resources allocated on treatment process, that will cause a decline in the resources allocated on following-Up process, and then when there is an increase in resources allocated on following-Up process, that will cause a decline in the resources allocated on treatment process.

5 Chapter 5 Model Validation

5.1 Validation Overview

The system dynamics modeling method is iterative, with many tests performed to analyze the model and build confidence in its utility. This approach yields insights into the links between system structure and behavior. The formal methods that persuade individuals to believe in a model are sometimes referred to as model validation (Richardson & Pugh III, 1981). In truth, there is no universally acceptable validation technique that a system dynamics model must follow in order to be declared verified (Yaman Barlas, 1996; Sterman, 2002).

According to (Y Barlas & Erdem, 1994) , validity in system dynamics corresponds to the model's internal structure rather than its output behavior. Because it is possible to get the "correct conduct for the wrong reason," behavior replication alone is insufficient to presume validity. Instead, if models have a purpose against which their validity may be tested, the validation process should be focused toward achieving the model's purpose.

Given validation's limitations due to its qualitative and iterative orientation, (Yaman Barlas, 1996) presented a structured progression as a guideline for conducting the model validity tests in three phases: direct structural testing, structure-oriented testing, and behavior pattern projection. Any of these tests, alone, is clearly insufficient as a determinant of model validity. They provide a strong filter when combined, capable of catching and screening out weaker models while permitting those that are most likely to represent anything near to truth. This criterion is followed by the model in this study. The processes for performing the testing are further discussed, along with explanations of the individual tests.

5.2 Structure Validity

5.2.1 Direct Structure Tests

Direct structural tests evaluate the model structure's validity by comparing it to knowledge about real-world system structure. This entails comparing each equation and logical function of the model with the relationships known about the real system. There is no simulation in these tests. The following tests fall under the theoretical structural test category, and they include comparing the model structure to generalized information about the system that exists in the literature, given the objective of this model as indicated in Chapter one.

5.2.1.1 Structure Confirmation Test

The purpose of this test is to match the model equations to the real-world relationships (Forrester & Senge, 1980). During the model-building process, the conceptual underpinning of the model is founded on a critical literature review on cancer treatment resilience and resource reallocation. The structure of how the cancer patient paths CPP conceptualized structure influences the demand on the health system is an example of structure-confirmation accomplished throughout the modeling phase. Patients who follow such a protocol will experience unnecessary delays, especially if they are in an emergency. At the same time, patients who require only follow-up or monitoring following basic therapy are given the same priority as those who require hospitalization. Detailed explanation of equations is attached in the documentation, in appendix C.

5.2.1.2 Parameter Confirmation Test

This evaluation ensures that all model parameters are appropriate and that each constant and variable has a meaningful true purpose. The parameter confirmation was continually compared to what was known in the literature, both conceptually and quantitatively.

The conceptual confirmation was carried out by finding the components in the literature that matched to the model's parameters. The quantitative verification was carried out by estimating the mathematical value of the parameter with sufficient precision and ranges. Some technical parameters are constructed only for modeling purposes, that parameter contains equations for modeling purpose. For example, some technical factors, such as "shock function," are modeled to portray the influence of shock on the model's behavior under risk conditions; this parameter also assures that the model can provide independent behavior when we need to perform policies without or with shock. Detailed explanation of equations is attached in the documentation, in appendix C. Examining the values for all the model's parameters allows the reader to have a more precise and trustworthy knowledge of the model, and we discover that the aggregated structure is suitable for the study aim.

5.2.1.3 Direct Extreme- Conditions Test

This test confirms that each model equations produces credible result under extreme conditions. The test was carried out by comparing the validity of the obtained values to what would happen in the real system under identical conditions (Senge & Forrester, 1980). This test's result may be inferred without the requirement for simulation; it is applied by reviewing each equation individually. The equations were run under severe circumstances for each flow in the model, tracking down to the stocks involved. For example, in the cancer treatment sector, each stock and flow has been tested to investigate if its value gives a reasonable result as it is conceptualized from the literature review of the CPP. Then, the used values have been tested under extreme conditions. The results of these tests are included in appendix B.

5.2.1.4 Dimensional Consistency Test

When the model is built, the dimension for each variable is provided; the dimensional consistency test reflects either unit inaccuracy or missing units. The system dynamics program used for this research (Stella Architect 2.1.3) completed the dimensional consistency test instantly since the model cannot operate unless all equations are dimensionally consistent. This test helps in assessing if the units on the left and right sides of each equation match without the use of arbitrary "scaling" parameters with no real-world value (Yaman Barlas, 1996; Sterman, 2002) .The model produced for this study is regarded as spatially coherent because it produces no unit error warnings when the simulations are conducted. A detailed description of the model equations is attached in the documentation at appendix C.

5.2.2 Structure -Oriented Behavior Tests (Indirect structure Tests)

This series of tests evaluates the structure's validity indirectly by using specific behavior tests on model-generated behavior patterns (Yaman Barlas, 1989; Senge & Forrester, 1980). These simulation tests are strong behavior tests that might assist the modeler in identifying potential structural faults.

5.2.2.1 Indirect Extreme- Conditions Test

This test is used to determine if the equations of the designed model reflect reasonable behavior under severe situations. For this evaluation, the Indirect Extreme Conditions test uses simulation. A very basic test would be to see what would happen if no new instances of cancer occurred; this test is carried out by using zero values for the three converters: Expected Fraction New Cancer Cases, back to System fraction, and Re-Cancer fraction. The formula is correct, as seen by the graph in *Figure 5:2* Total New Cases of Cancer Rate remains zero.[4]

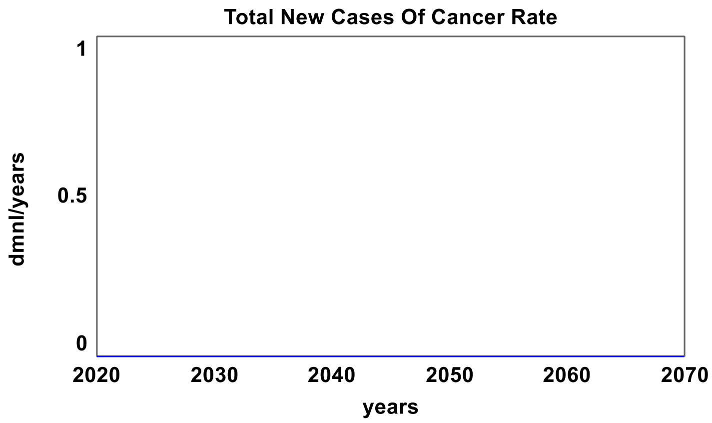


Figure 5:1 Total New Cases of Cancer Rate with Zero Expected Fraction New Cancer Cases

The system's intended behavior would be that there is no rise in the total population with cancer, so the pressure on the health sector will be at its lowest level. Conducting this test gives the resultant graphs that we see in *Figure* ***5:2.*** On the left, pressure on the health system starts with a value of 15 at the beginning of the simulation period, then it decreases decreasingly to reach the value of zero at 2030. The reason for that is the initial value for the stock population with cancer, the stock treated

[4] For simplicity, Total New Cases of Cancer Rate is used to do this test instead of doing it for the aggregated inflow "New Cases of Cancer Rate," because the latter one includes the ten rates that are for each age group. For detailed figures, please see appendix A.

and needing follow-up, and the stock recovered population. These stocks have been initiated to their value in 2020, so there will be some patients who need treatment. Even if there are no new cases (when the Indirect Extreme-Conditions Test is done), those patients will cause that pressure. The same reason also causes the behavior of the Total Population with Cancer (Right) in *Figure **5:2.*** At the beginning of the simulation period, this value is at its initial value of around 38,000 people, but the curve starts to decrease increasingly as the number of new cases of cancer is zero. The total population with cancer reaches zero in 2030 and continues with zero value to the end of the simulation period.

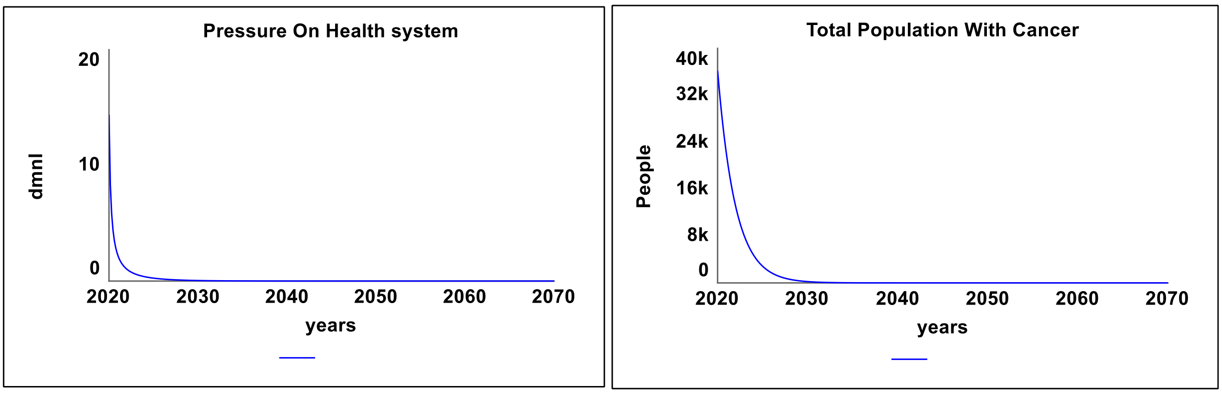


Figure 5:2 Pressure on Health System (Left), Total population with Cancer (Right) under Testing with Zero Expected Fraction New Cancer Cases, back to System fraction, and Re-Cancer fraction

5.2.2.2 Behavior Sensitivity Test

This test "entails determining the parameters to which the model is extremely sensitive and determining whether the real system would exhibit equally high sensitivity to the corresponding parameters " (Yaman Barlas, 1996). Therefore, the model's parameters are projected to fall into three categories: those that are likely to be sensitive, those that give leverage points for policy suggestions and, as such, should be sensitive, and those that are not expected to be sensitive. The sensitivity test focuses on the latter category. In this scenario, the test tries to not only confirm this repetition of the model but also to provide important insights into which parameters we might study further through more data gathering for verification. The results of these tests are included in appendix B.

5.2.3 Population dynamics Validation

Depending on data from (ssb.no, 2021), the researcher reproduced the reference mode for population dynamics. ***Figure 5:3*** depicts the reference mode for Population-West Norway (Read Curve) and behavior produced by the CTR Model (Blue Curve). The reader could argue that there is a slight difference between both behaviors. There are some reasons for that. Firstly, data projected by (ssb.no, 2021) depends on different measures than the system dynamics approach. Secondly, Statistics Norway publishes three alternatives of projections for expected life expectancy, which are: high alternative (HHH), main/medium alternative (MMM), and low alternative (LLL). The researcher chooses to use MMM (Medium alternative, which assumes the medium level for each component) because this is what is assumed to be most plausible. The researcher preferred to use only one alternative to follow when she gathered data—that is, the medium alternative—to avoid complexity or confusing the reader with different scenarios for expected data.

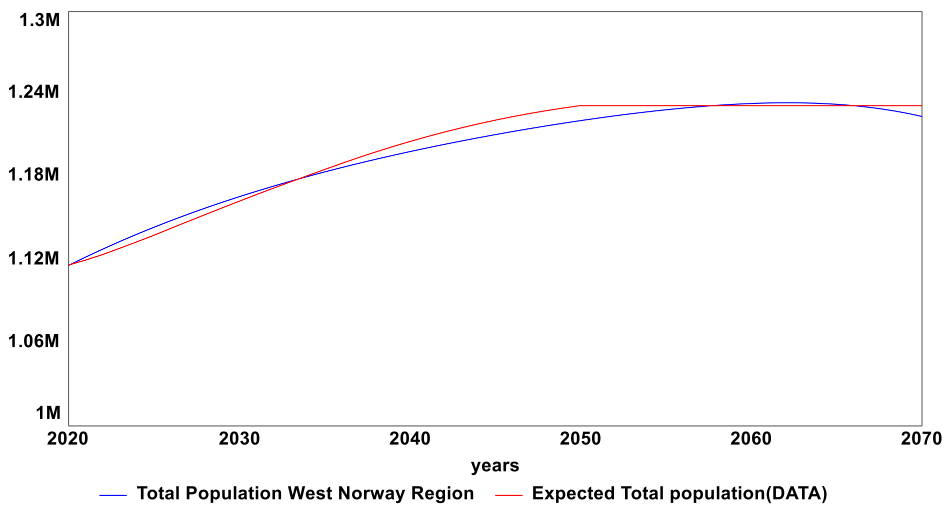


Figure 5:3 Behavior for total Population West Norway produced by the CTR Model and Expected Total Population extracted from (ssb.no, 2021)

The last reason for getting a slight difference between the two behaviors is the unavailability of some needed data. For example, there are some values that have been assumed by the researcher as it has been explained in the documentation in appendix C. Dividing the population into 10 age cohorts increases the difficulty in finding data for each group. Also, finding data for the population in west Norway forced the researcher to assume some values, either by using the average values or expecting some values depending on historical data for variables.

5.3 Cancer Treatment Process Validation

This model is the first iteration for presenting the CHSR Model, as mentioned in the problem statement and the literature study. This sector was intended to represent the notion of a cancer treatment system in western Norway. Although there is no direct data for each stock and flow utilized, the researcher used data that forecasts the amount of cancer patients, for example, or cancer deaths for the entire country. Appendix C of the documentation contains an explanation for each stock and its flow-initiated or assumed value.

5.4 Resources Behavior Validation

There are many other resources that could be included in this sector to give it more validity, but to avoid complexity in modeling, the researcher used only data for specialized doctors and nurses. Data found on the Norwegian websites (ssb.no, 2021) or (sb.kreftregisteret.no, 2022) gives a general number for the whole health personnel in health sectors, but not for the cancer treatment sector. This sector has been modeled based on the researcher's estimations of the number of currently hired specialized doctors and nurses. At the same time, historical data for health personnel in general shows the same pattern of behavior, which depends on the allocation or loss of resources. Both historical and projected data for health personnel emphasize the high demand for health personnel that is produced by the CHSR model.

6 Chapter 5 Behavior Analysis

6.1 Behavior Analysis Overview

To obtain literally the entire results of the CHSR model, we simulated it from 2020 to 2070. The model's capacity to provide CHSR is put to the test in this thesis. Two distinct experiments will be carried out to put this to the test. The model will first be simulated before a shock or crisis occurs, and then it will be simulated under a shock scenario. The system is expected to experience a shock state between 2040 and 2045. The choice of 5 years as the shock period is reasonable since most pandemics or disease outbreaks that create delays in healthcare systems last 5 years on average. Furthermore, the magnitude of 5 years is appropriate when compared to the simulation time of 50 years. Based on epidemic history, most shocks or crises endure on average 5 years. It might be less or more, but in most circumstances, this is the average. Choosing the year 2040 to begin the shock is also fair because it falls halfway through the simulation period. The changes that occurred before and after this period may be properly addressed and studied.

As it is shown in the documentation at appendix C, the SMOTH1 function has been used to determine the main fractions that cause a decrease in or increase in the inflows or outflows of the stocks. These functions provide logical results, as there is a delay in systems' adoption of changes.

Time to adopt policy1 or policy 2 is assumed to be 1 if this policy is active, but 5 years if it is not active, as an indication of the system's delay and slow response to improve its performance. The scenarios analyzed in this thesis used the time to adopt the policy to be 1 year, but the reader can refer to appendix A to see how the behavior of the main KPI changes when changing this time. In Figure 6:1 Simplified part of Cancer Treatment process sector, with focusing on policy variables. This structure, shows how the structure causes the behaviors we will see later when discussing the behavior of KPI.

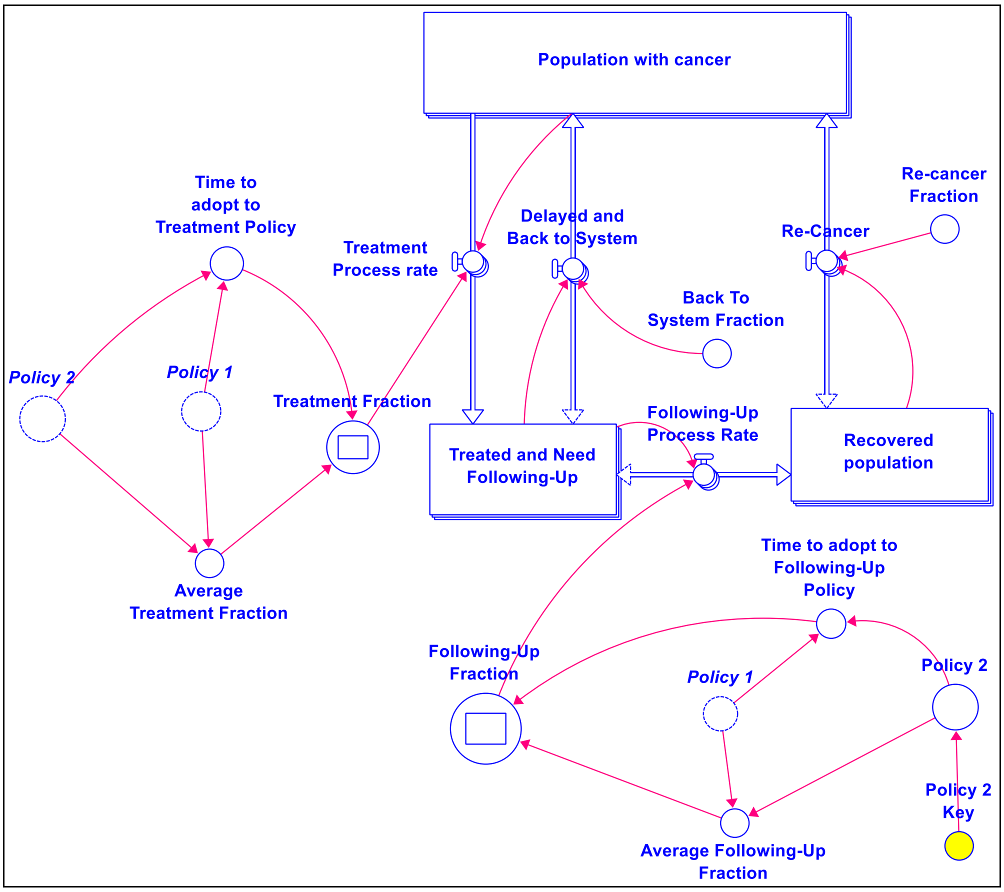


Figure 6:1 Simplified part of Cancer Treatment process sector, with focusing on policy variables.

Testing the behavior of the KPI of CHSR model when there is no shock in the system provides decision makers with insights to explore the level of resilience in cancer treatment system performance in different scenarios. Given the expected demand in Cancer treatment that is discussed in the introduction and problem statement of this research, it is necessary to suggest policies that is assumed to build CHSR, such system prepare for future demand even there is no crises. Therefore, we see in **Table 2** the conditions at which the built cancer healthcare system performs. The reader can refer to appendix C for more explanation for each parameter that affects the behavior of the KPI.

6.2 Scenarios without Shock

Table 2 Scenarios Without Shock

	Business as Usual	Policy 1	Policy 2
Treatment Fraction	0.5	0.8	0.6
Following-Up Fraction	0.4	0.2	0.5
Fraction Of Following-Up Resources	0.5	0.1	0.5
Fraction Of Treatment Resources	0.5	0.9	0.5
Total Resources Allocated	Initial Values	Initial Values	Initial Values + 25% of initial values
Average Fraction of Resources Lose	0.03	0.03	0.03
Average Fraction of Resources allocation	0.04	0.04	0.04
Back to system Fraction	0.1	0.1	0.1

Table 2 summarizes the results of running the model before any shock that is caused by emergency conditions like disease pandemic or epidemic that causes delays in treatment of Cancer patients. In ***Figure 6:2*** we see the resulted behaviors for the KPI in each scenario.

6.2.1 Scenario 1 Business as usuell

In this scenario, there is no policy adopted and the CHSR performs regarding initial values that are assumed and gathered from data sources. ***Figure 6:2*** displays the behavior of the resulting graphs. We conclude that these behaviors are predicted based on the assumed values for parameters in **Table 2** . Prior to enacting any policy, overall cancer deaths are greater in the base run when compared to alternative scenarios. More discussions concerning these findings will be discussed when policy scenarios are presented.

6.2.2 Scenario 2 Policy 1:

Allocating more resources to the cancer treatment phase than the baseline and allocating fewer resources to the follow-up process than the baseline.

In this scenario, our model will examine the effect of raising the proportion of resources provided from 0.5 to 0.8 percent from the baseline. This means that the system will implement a policy that will expand the number of specialist physicians and nurses who treat cancer patients by 30%. Simultaneously, the system will cut the percentage of resources dedicated to the follow-up phase from 0.4 percent to 0.2 percent. That means that under the same strategy, the number of expert physicians and nurses who monitor cancer patients would be reduced by 20%. As described in the study's literature analysis and problem statement, those patients are likely to require less priority. The implementation of this policy will be explored further in This thesis's implementation section.

6.2.3 Scenario 3 Policy 2: Recruiting 25% more nurses and specialized doctors than were initially hired

In this scenario, our model will examine the effect of raising the proportion of total resources by 25% from the baseline. This means that the system will implement a policy that will expand the number of specialist physicians and nurses who treat and monitor cancer patients without considering any priority in the patient's condition or level of cancer tumor. The implementation of this policy will be explored further in this thesis's implementation section.

Choosing a percentage of 25% is reasonable because hiring more health personnel is common in health systems under commonly used policies, and many studies have concluded that the increased demand in healthcare systems necessitates the importance of hiring more staff , see for example (Lin et al., 2021; Trellevik, 2008) . This thesis tests the difference in KPI behavior when systems adopt reallocation policies or recruit more health personnel staff policies.

In this thesis, combining both policies is not an alternative. The reason behind that is the incompatibility between both policies. If the suggested policies are complementary policies, then we can combine both, but each policy depends on a different approach. The nearest alternative to the scenario of combining both policies is to increase the fraction of following-up resources by, for example, 50% and to increase the fraction of treatment resources by 30%. That increase in resources will be added to the CHSR model by external resources, not the resources that are currently in the system. To avoid complexity in modeling and more confusing equations, this research will discuss the adoption of 3 scenarios as in **Table 2**.

Behaviors of main KPI when the CHSR Model is simulated before the shock

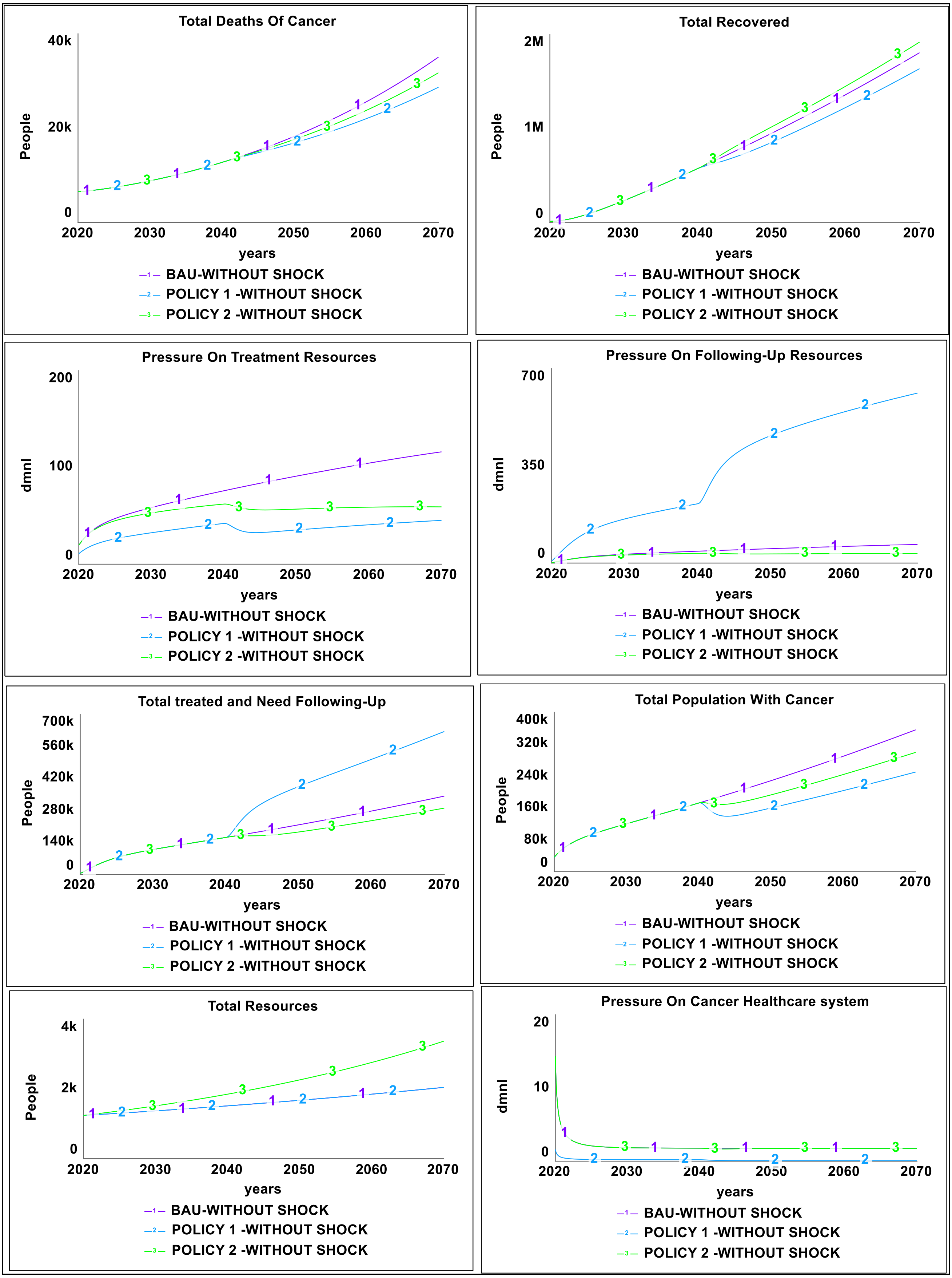


Figure 6:2 Behavior of main KPI when the CHSR Model is simulated before the shock

6.3 Scenarios with Shock

Figure ***6:1 Simplified part of Cancer Treatment process sector, with focusing on policy variables.***

Figure 6:3 Simplified part of Resources Management sector, with focusing on policy and shock variables

This structure, shows how the structure causes the behaviors we will see later when discussing the behavior of KPI during the shock.

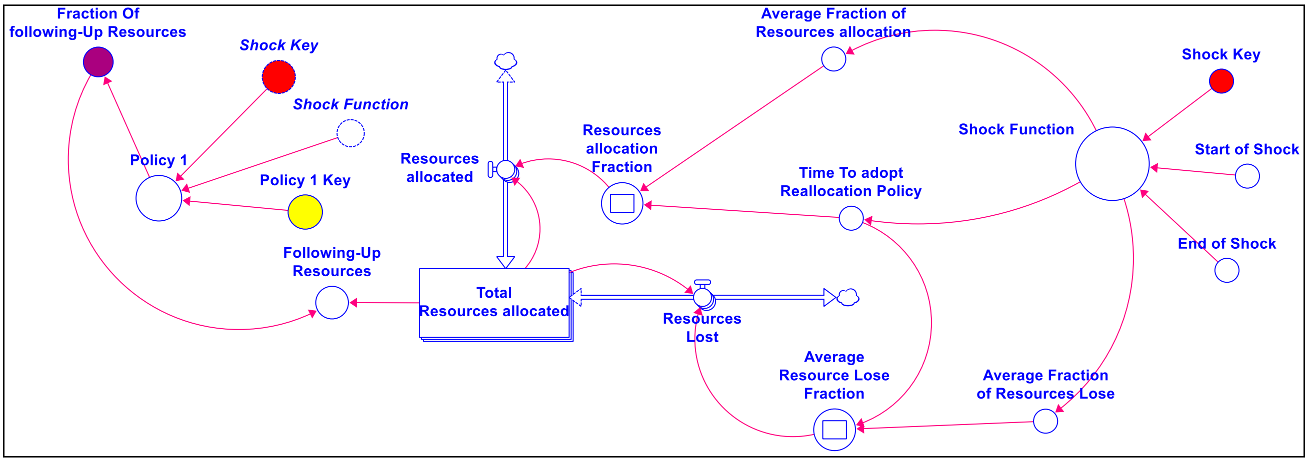


Figure 6:3 *Simplified part of Resources Management sector, with focusing on policy and shock variables*

Table 3 Scenarios with Shock

	Business as Usual	Policy 1	Policy 2
Treatment Fraction	0.5	0.8 0.5	0.6 0.5
Following-Up Fraction	0.4	0.2 0.4	0.5 0.4
Fraction Of Following-Up Resources	0.5	0.1 0.5	0.5 0.6
Fraction Of Treatment Resources	0.5	0.9 0.5	0.5
Total Resources Allocated	Initial Value	Initial Value	Initial Value+ 25% of initial value
Average Fraction of Resources Lose	0.06 0.03	0.06 0.03	0.06 0.03
Average Fraction of Resources allocation	0.02 0.04	0.02 0.4	0.02 0.04
Back to system Fraction	0.3	0.3	0.3

	0.1	0.1	0.1

Behaviors of main KPI when the CHSR Model is simulated with shock

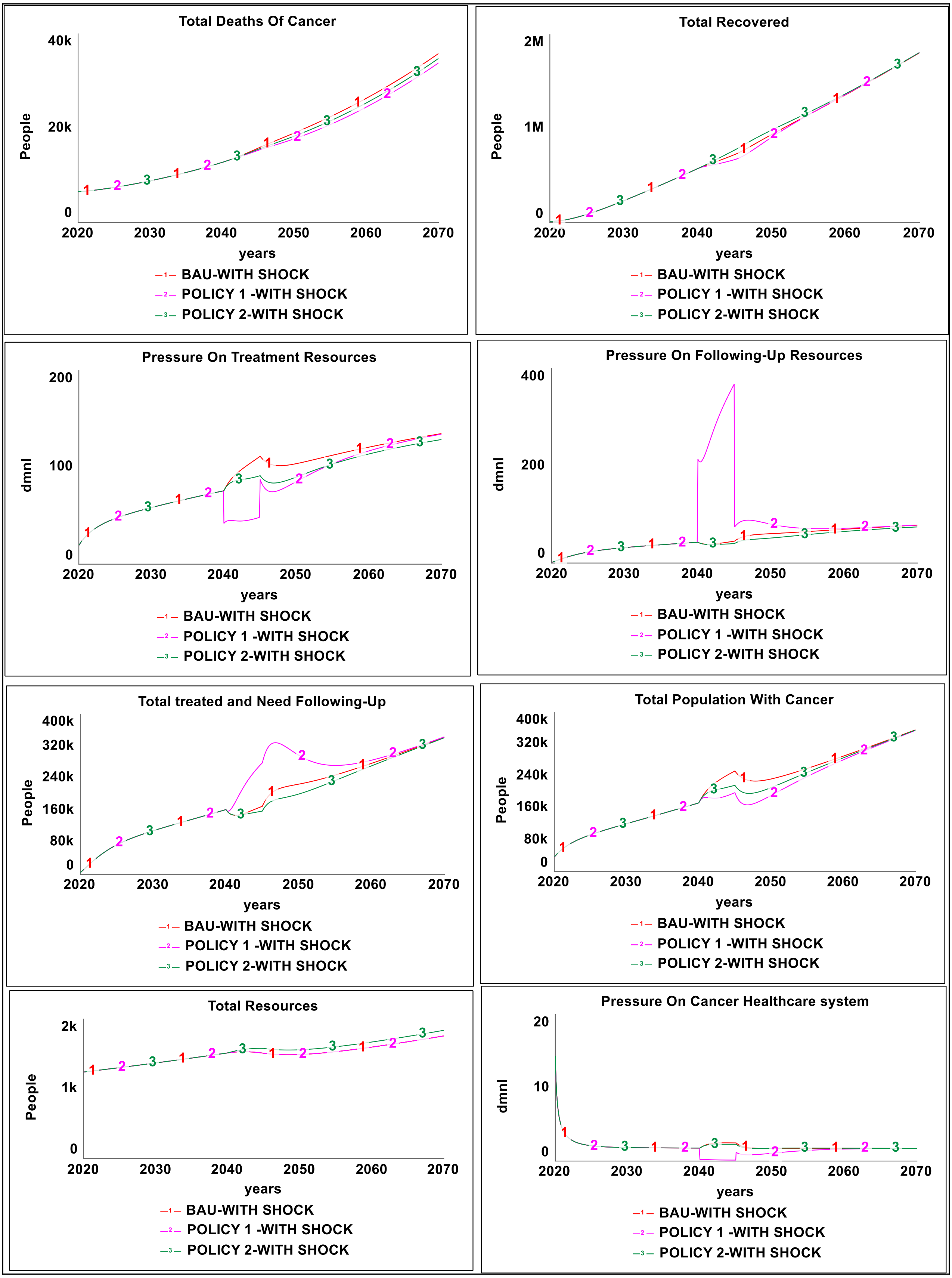


Figure 6:4 *Behavior of main KPI when the CHSR Model is simulated with shock conditions.*

6.3.1 Scenario 1 Business as usuell

In this scenario, there is no policy adopted and the CHSR performs regarding initial values that are assumed and gathered from data sources. Appendix A contains more details about

parameters and key values at the base run.

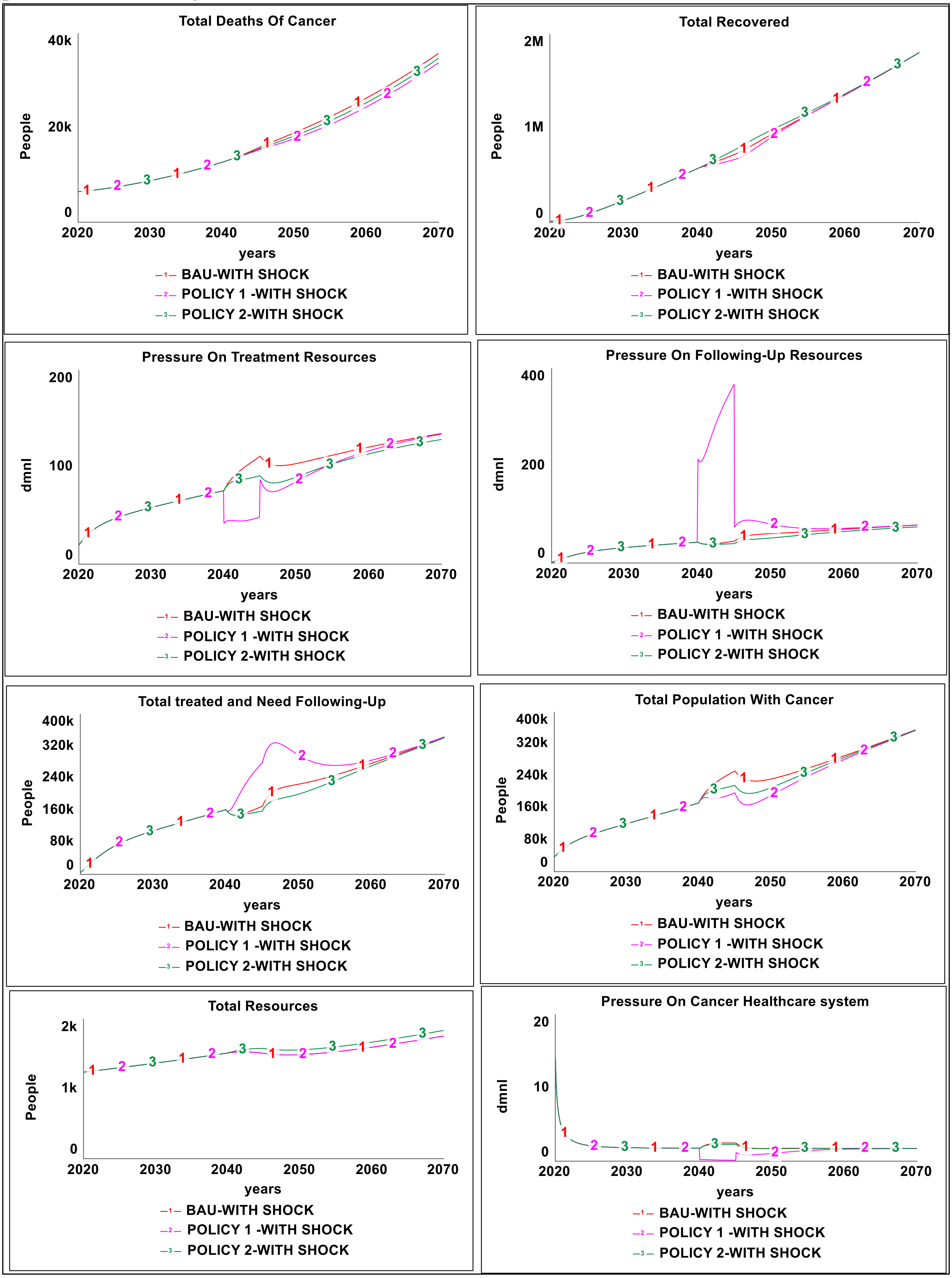


Figure 6:4 displays the behavior of the resulting graphs. We conclude that these behaviors are predicted based on the given values for parameters in **Table 3**. Prior to enacting any policy, overall cancer deaths are greater in the base run when compared to alternative scenarios. More discussions concerning these findings will be discussed when policy scenarios are presented

The shock phase will affect the system between the years 2040 and 2045, as stated in the analysis review. The shock function variable in the model has represented this shock.

IF Shock_Key=1 THEN STEP(1, Start_of_Shock)+STEP(-1, End_of_Shock) ELSE 0

The shock effect is seen in the behavior of variables, as shown in

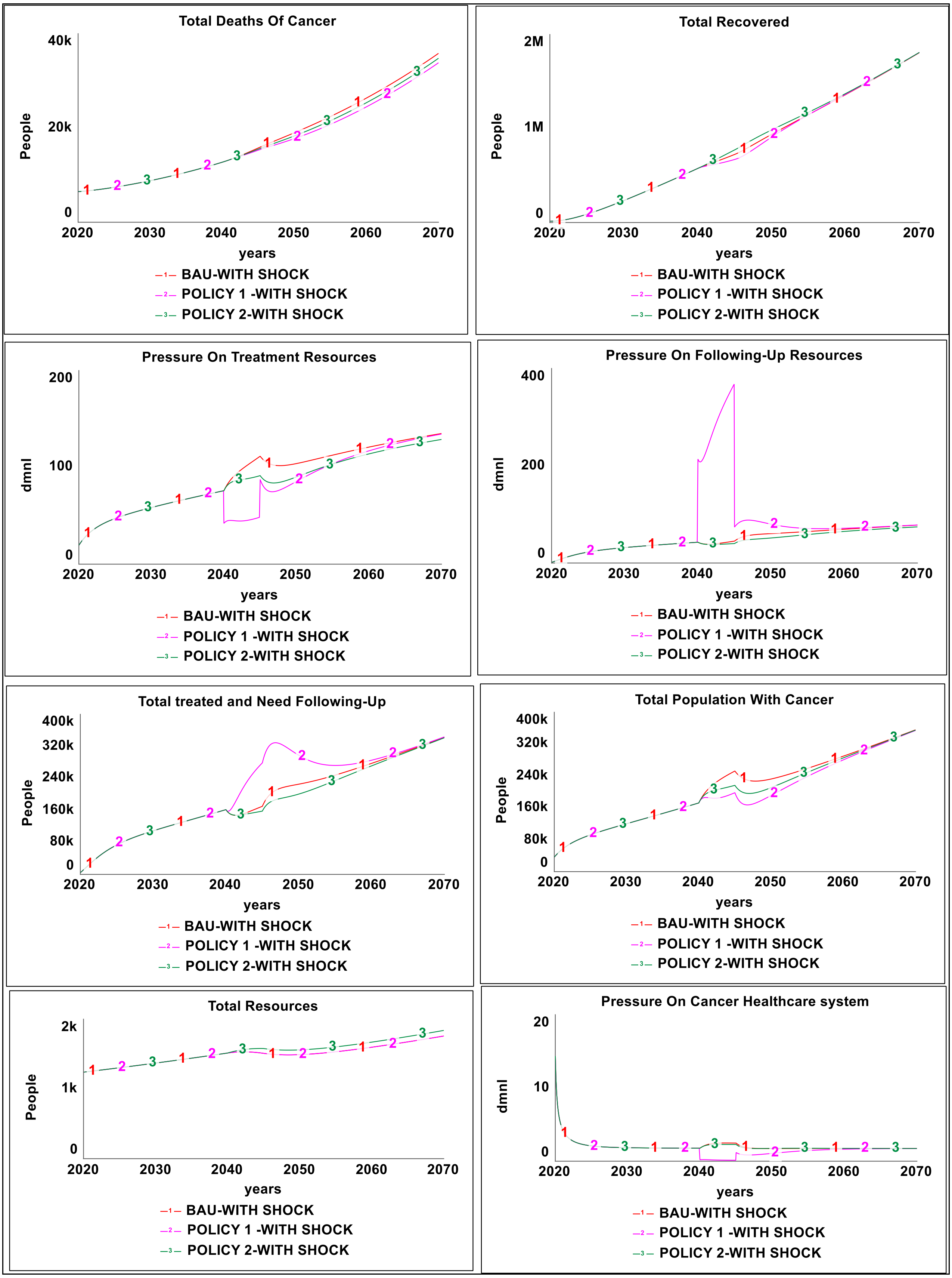


Figure 6:4 During the shock phase, there is a rise in the demand for cancer treatment resources and the cancer healthcare system. In addition, the overall cancer population is growing. However, the number of persons who are treated and require follow-up has significantly dropped. However, we can observe that the shock had a minor impact on the number of those who had recovered. To compare the baseline state before and after the shock, graphs comprising only these two scenarios are included in Appendix A.

6.3.2 Scenario 2 Policy 1: Allocating more resources to the cancer treatment phase than the baseline and allocating fewer resources to the follow-up process than the baseline.

In this scenario, the system will be faced with a shock during the shock period between the years 2024 and 2045. In this case, our model will investigate the impact of increasing the proportion of resources provided from 0.5 to 0.8 percent of the baseline. This means that the system will implement a policy that will increase the number of specialist physicians and nurses who treat cancer patients by 30%. Simultaneously, the system will cut the percentage of resources dedicated to the follow-up phase from 0.4 percent to 0.2 percent. That means that, under the same strategy, the number of expert physicians and nurses who monitor cancer patients would be reduced by 20%.

In **Table 3**, variable values that are in red mean that these values are only during the shock period, which is five years. While the values in black indicate that they are for variables before 2040 and after 2045.

This policy will start to be active from year 2040, the start of the shock period. Then we see in the resulted graphs that the effect of this policy continues through the whole simulation period. The aim of this simulation is to show the effect of policy when there is a shock and to give insights to decision makers; to explore how systems respond to shocks; and how adoption of policies can mitigate the pressure on systems. Given that goal of the thesis, graphs comprising only the scenarios of the model when applying policy 1 with and without the shock are included in Appendix A.

6.3.3 Scenario 3 Policy 2: **Recruiting 25% more nurses and specialized doctors than were initially hired**

In this scenario, the system will be faced with a shock during the shock period between the years 2024 and 2045. Our model will examine the effect of raising the proportion of total resources by

25% from the baseline. This means that the system will implement a policy that will expand the number of specialist physicians and nurses who treat and monitor cancer patients without considering any priority in the patient's condition or level of cancer tumor. This policy will start to be active from year 2040, the start of in the shock period, then we see in the resulted graphs, the effect of this policy continue through the whole simulation period.

As this thesis tests the difference in KPI behavior when systems adopt reallocation policies or recruit more health personnel staff policies, graphs comprising only the scenarios of the model when applying policy 2 with and without the shock are included in Appendix A.

7 Chapter 7 Policy alternatives Analysis:

To achieve the aimed goal of conducting this thesis, this chapter will discuss the two suggested policies that aim to answer the fifth and sixth research questions.

7.1 Policy Alternative 1: Allocating more resources to the cancer treatment phase than the baseline and allocating fewer resources to the follow-up process than the baseline.

We can observe in this policy that dedicating more resources to the cancer treatment phase improves the overall efficiency of the cancer healthcare system. In other words, we created a robust system that decision-makers may consider when planning for the predicted demand for cancer treatment. The major loop B2, which has been strengthened by the implementation of this program, reduces the need for cancer treatment resources. Even while adopting this policy has raised the pressure on the following-up phase, as stated in the literature review of home-based care and the following-up processes, we observe that this pressure will have less of an effect on the following-up resources. This policy option increases the number of specialist physicians and nurses who treat cancer patients by 30%. Simultaneously, the system will cut the percentage of resources dedicated to the follow-up phase from 0.4 percent to 0.2 percent. We see that the change that is caused by this policy is not big when we compare the percentages with each other. But the effect we get is worth adopting it. Decision makers can evaluate the suitable reallocation procedure. This model provides the idea of reallocation of resources, but systems should be flexible to changes.

Applying this policy is more feasible when the system is exposed to shocks. As we have seen in the scenario test, the effect of adopting such a policy enhanced the efficiency of the cancer treatment system during the shock period and in the following years. Delays are expected in the system, so we could not see the effect of the suggested policy during the whole shock period. As we saw in the scenario analysis test and graphs, the effect can be seen after some delay, at least the year that the system requires to adopt policy, as we saw in the scenario analysis test and graphs.

7.2 Policy alternative 2: Recruiting 25% more nurses and specialized doctors than were initially hired

In this policy, we see the effect of raising the proportion of total resources by 25% from the baseline. This means that the system will implement a policy that will expand the number of specialist physicians and nurses who treat and monitor cancer patients without considering any priority in the patient's condition or level of cancer tumor. If we evaluate this policy separately from the first policy, we conclude that it is effective both in systems with shocks and without shocks. The behaviors we see in the scenario analysis results show that this policy has a positive effect on the behavior of the entire cancer treatment system. But the question is: is it that policy causes resilience to the system? As it was introduced in the literature review, resilient systems should be able to perform during crises by using the available resources. As we see in this policy, we did not depend on the current resources that we have in the system. In contrast to the first policy option, we depended on external resources by hiring more resources. As we can see in *Figure 7:1 Total resources (Left) and pressure on Cancer healthcare system behaviors at Policy 2*

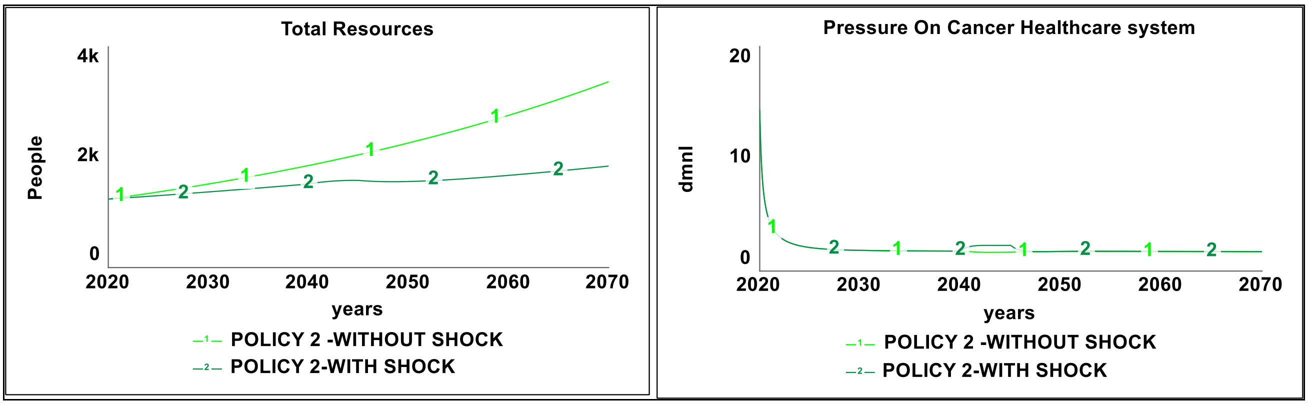


Figure 7:1 Total resources (Left) and pressure on Cancer healthcare system behaviors at Policy 2

8 Chapter 8 : Conclusions

In this study, we used a system dynamic approach to find out the feasibility of reallocating resources in the cancer healthcare system. In this model, we extracted the scenarios that show the behavior of the KPI that shows to what extent reallocating the resources gives decision makers with insights to build a resilient cancer treatment system that can fulfill the demands of patients in the future and at the current time.

8.1 Answer to Research Questions:

In the literature review, we answered the first question of the research questions, and we see in detail the difference between treatment and the following-up process. We have seen in the policy analysis and scenario analysis the effect of adopting resource allocation policies, and that answers the second part of the first question.

In the first chapter, we discussed the meaning of resilience in health sectors, and then we saw the practical application of such a concept in adapting policies that suggest allocating more resources to treatment patients. And that answers the second question in this research.

In the model description and scenario analysis, we have seen the application of the system dynamics approach to achieve CHSR, so we get an answer to the third research question.

From the literature review and the model description, we get answers to the fourth question of our research.

In the policy analysis chapter, we discussed the policy options that can be identified to achieve CHSR in the health sector in West Norway, and that answers the second part of the fourth question in this research.

We have seen in the scenario analysis the key performance indicators that decision makers can check when they evaluate the feasibility and rationality of introduced policies, and that answers the sixth research question.

By simulating the model, we see that the older age groups have more demand on the cancer treatment sector, and that answers the last question of our research.

8.2 Limitations and Further Research

This study, it may be argued, is a beginning point for a much bigger conversation about resources reallocation. However, it should be noted that this was a pilot study, and more research is needed to determine the true benefit of resource reallocation on cancer treatment resilience for cancer patients and health sector planning.

The limited data that could be collected is one of the biggest challenges to conducting such research. Also, the sensitivity of cancer disease to treatment and medication could cause difficulty in adopting any policy before evaluating its validity.

One of the major challenges in conducting such research is that the researcher intends to test resource reallocation from an administrative standpoint. This is not easy to do when we have to test medical results because cancer disease has many types and degrees of tumor stages. This research could be enhanced in the future by specifying its feasibility by testing it with a specific type of cancer disease.

Such a model needs to add more sectors in the future to get more interactions between the cancer treatment sector and other health sectors in west Norway.

The main point that the researcher emphasizes is that even with the limitations of this study and the limited data sources, we can improve by this model that reallocating resources is a fundamental approach in management, as we see that applying the second policy requires more external resources to be added while the first policy has used the current resources.

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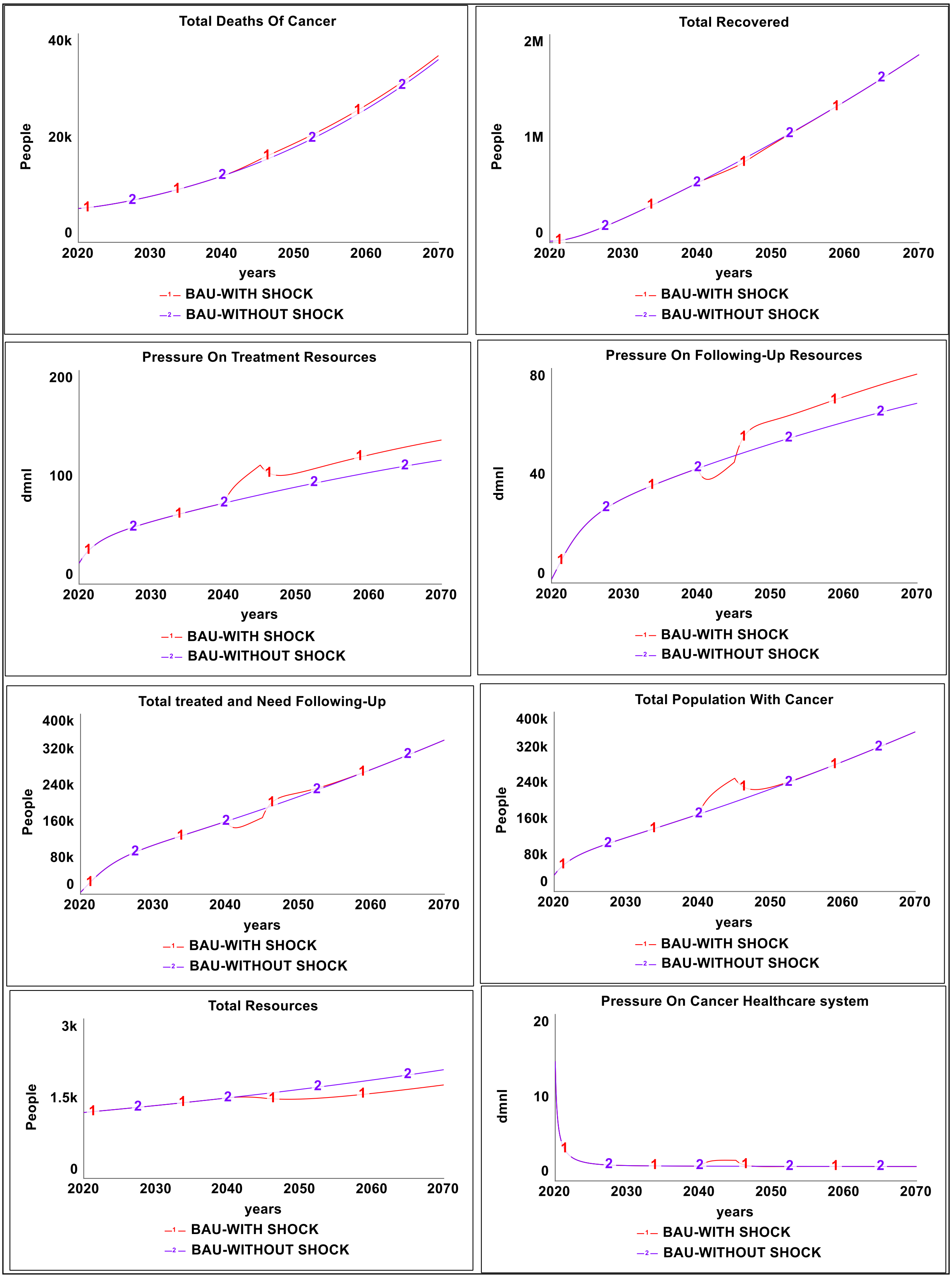
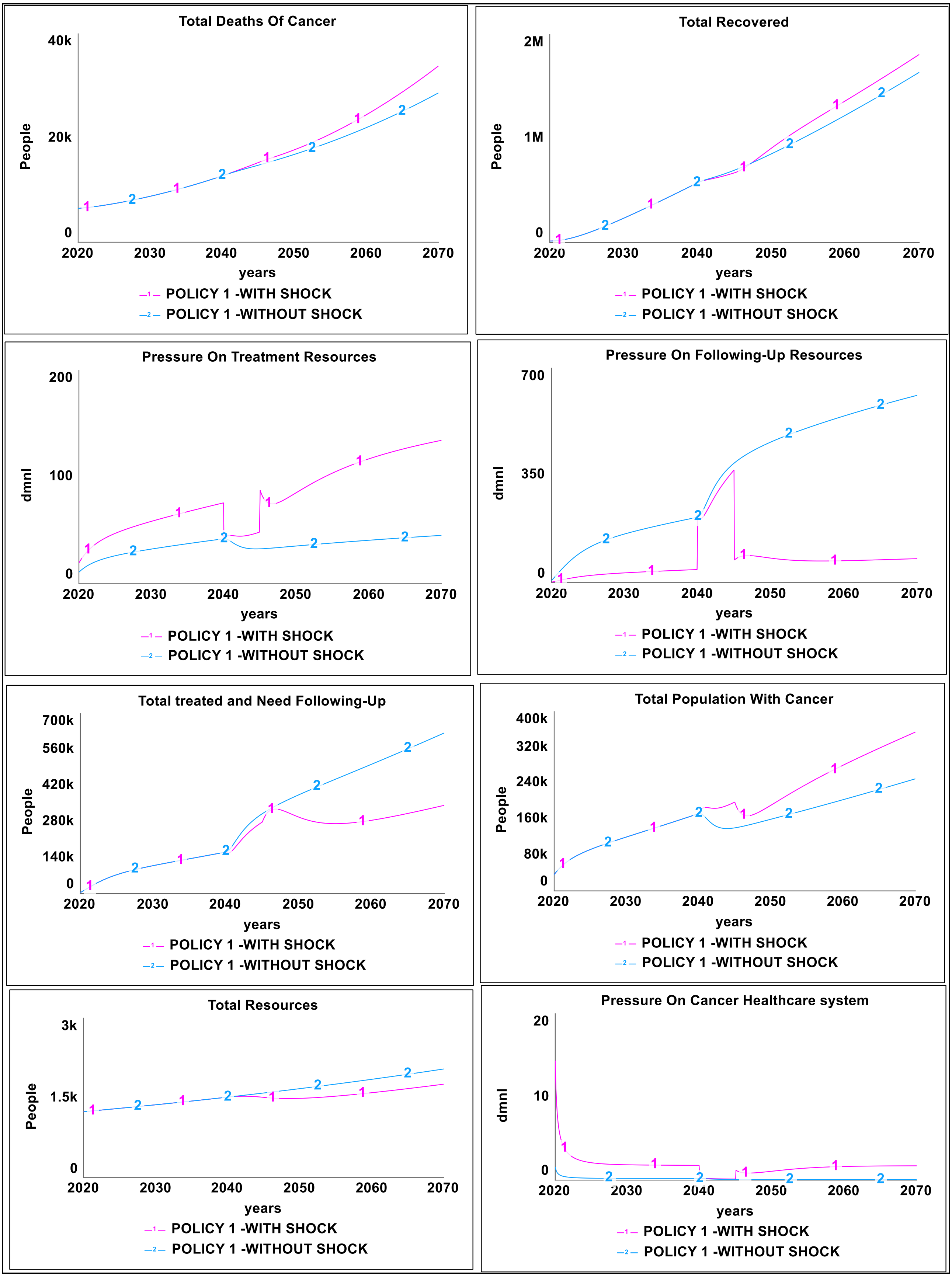
Appendix A: The three scenarios before and after the shock.

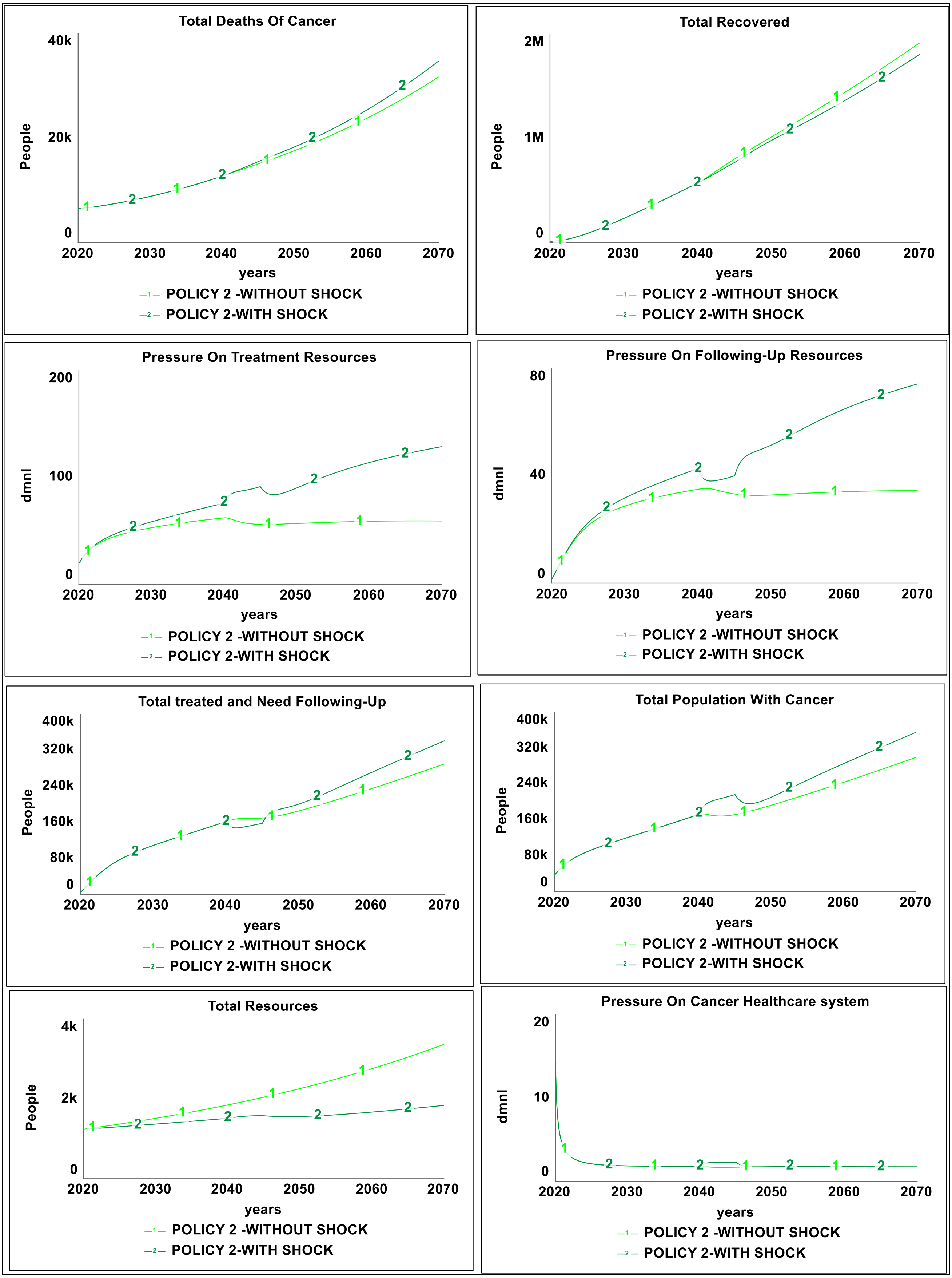
KPI behavior in the baseline scenario before and after the shock:



KPI behavior in the second scenario “Policy 1” before and after the shock:



KPI behavior in the third scenario “Policy 2” before and after the shock:

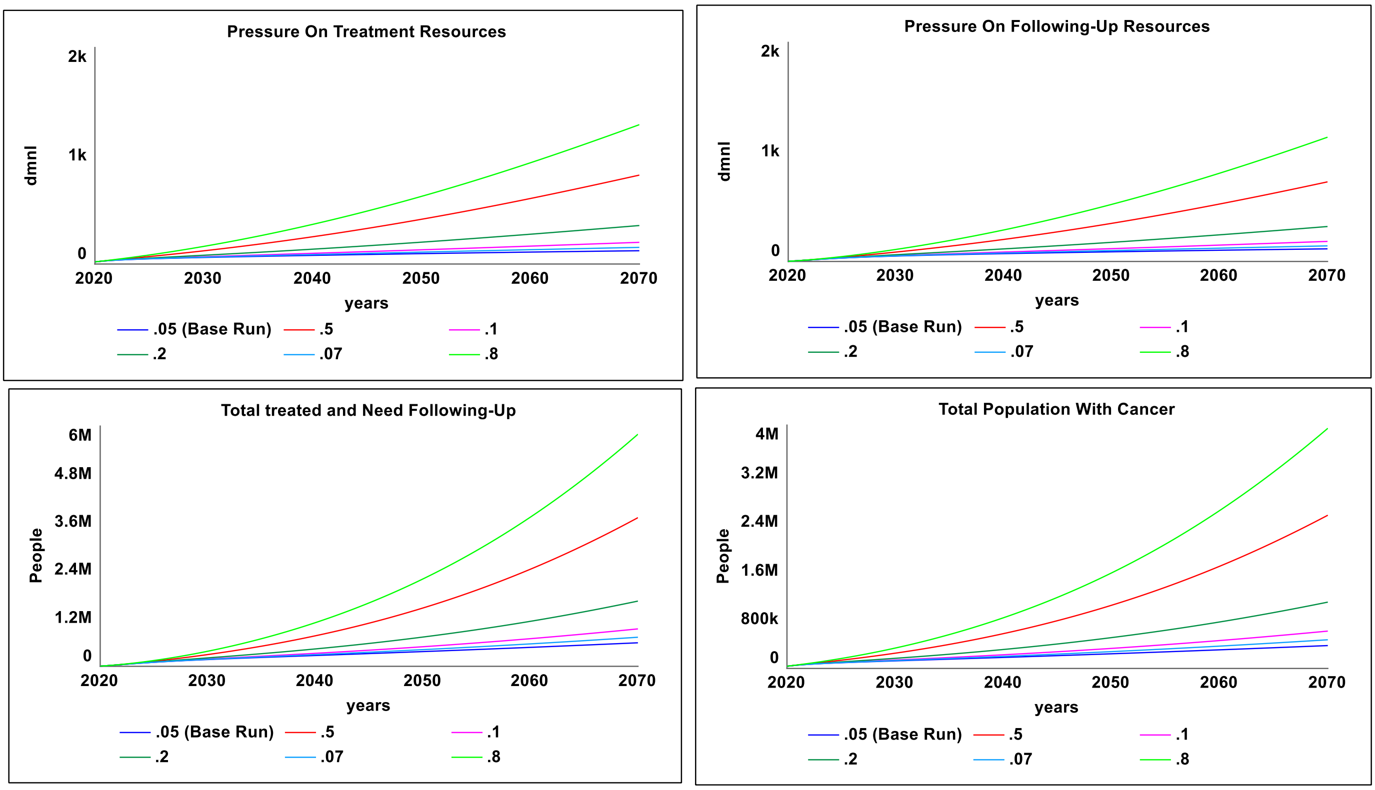


Appendix B: Sensitivity Tests

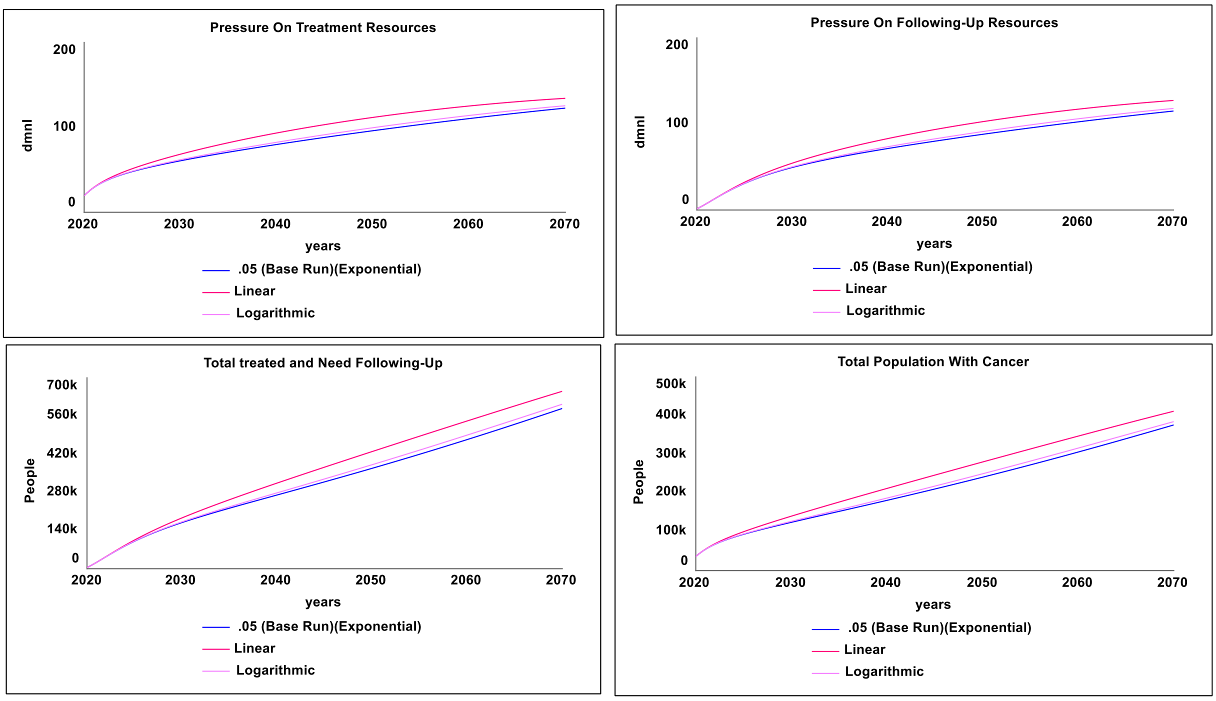
Cancer Treatment Process Sector					
	Converter	Value	Range	Sensitivity Level	Notes
1.	Expected Fraction of New Cancer Cases (Graphical Function)	Max=0.05 Min= 0.035	For Max. Value 0.04-0.8	High	
2.	Expected Fraction of New Cancer Cases (Graphical Function) Sensitivity Test for Shape of Curve	Exponential Max=0.05 Min= 0.035	Logarithmic- Linear - exponential	Medium	
3.	Expected Fraction of Deaths of Caner	Max=0.004 Min= 0.0026	For Max. Value 0.004-0.9	High	
4.	Expected Fraction of Deaths of Caner (Graphical Function) Sensitivity Test for Shape of Curve	Max= 0.004 Min= 0.0026	-Logarithmic Decay -Linear Growth -Exponential Growth	No	
5.	Average	6	1-10		

	Treatment Delay				

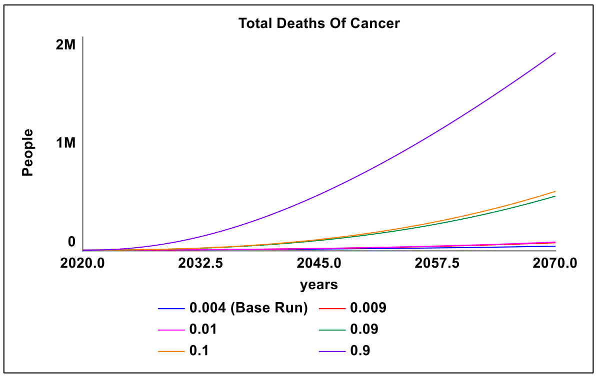
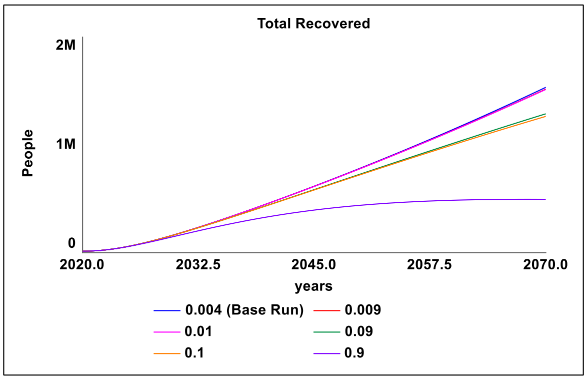
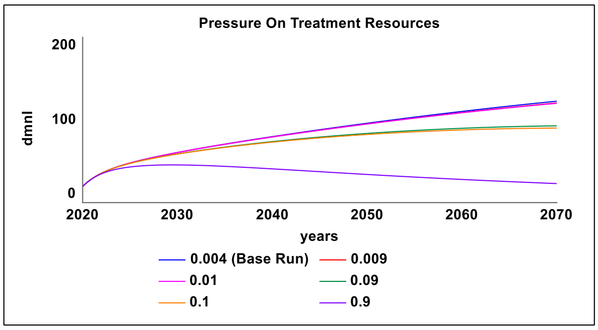
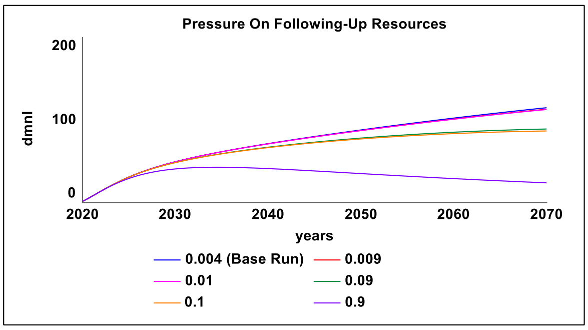
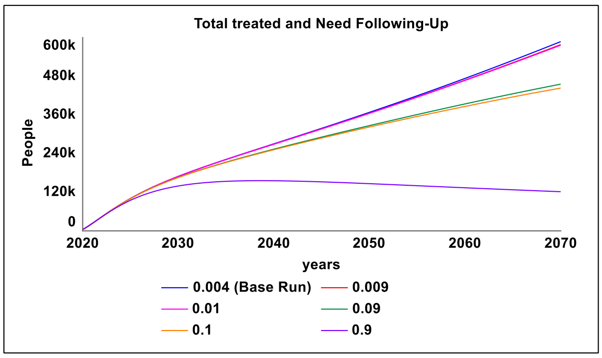
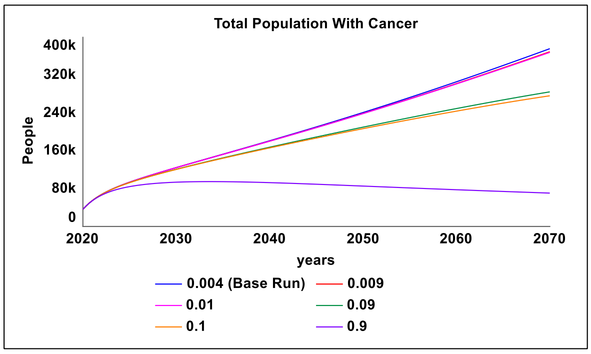
1. Expected Fraction of New Cancer Cases (Graphical Function) Sensitivity Test for maximum Value



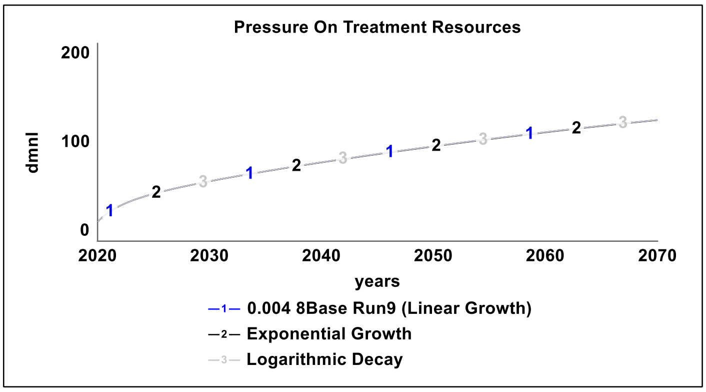
2. Expected Fraction of New Cancer Cases (Graphical Function) Sensitivity Test for Shape of Curve

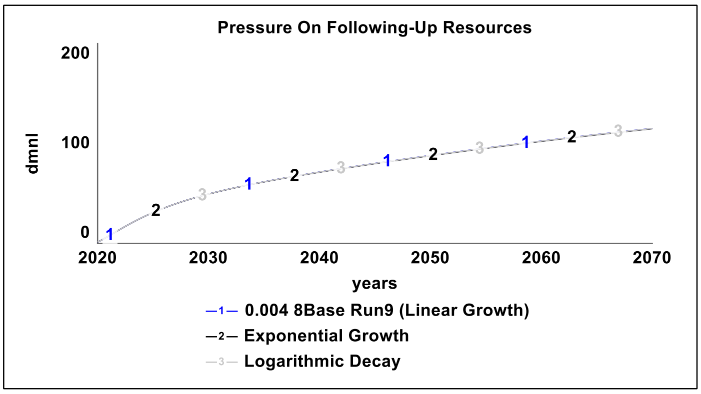


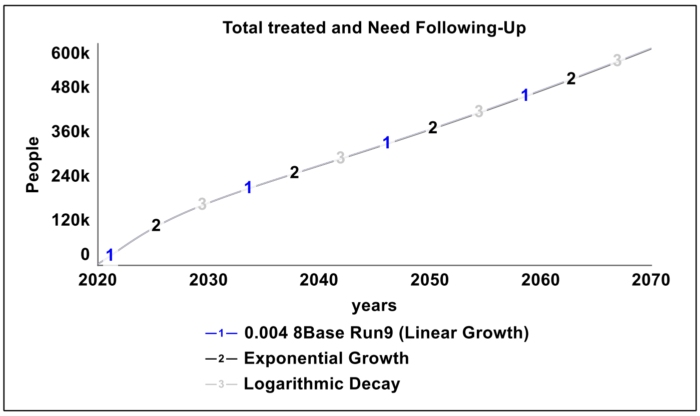
3. Expected Fraction of Deaths of Caner (Graphical Function) Sensitivity Test for maximum Value

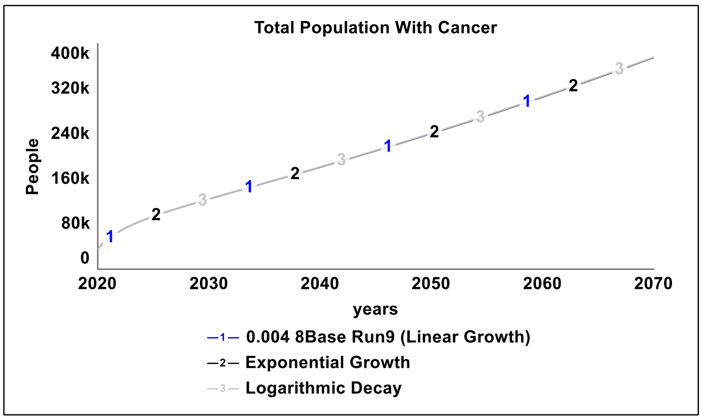

Total Deaths Of Cancer
2M
1M
0
People
2020.0
2032.5
2045.0
2057.5
2070.0
years
0.004 (Base Run)
0.009
0.01
0.09
0.1
0.9

Total Recovered
2M
1M
0
People
2020.0
2032.5
2045.0
2057.5
2070.0
years
0.004 (Base Run)
0.009
0.01
0.09
0.1
0.9

Pressure On Treatment Resources
200
100
0
dmnl
2020
2030
2040
2050
2060
2070
years
0.004 (Base Run)
0.009
0.01
0.09
0.1
0.9

Pressure On Following-Up Resources
200
100
0
dmnl
2020
2030
2040
2050
2060
2070
years
0.004 (Base Run)
0.009
0.01
0.09
0.1
0.9

Total treated and Need Following-Up
600k
480k
360k
240k
120k
0
People
2020
2030
2040
2050
2060
2070
years
0.004 (Base Run)
0.009
0.01
0.09
0.1
0.9

Total Population With Cancer
400k
320k
240k
160k
80k
0
People
2020
2030
2040
2050
2060
2070
years
0.004 (Base Run)
0.009
0.01
0.09
0.1
0.9

4. Expected Fraction of Deaths of Caner Sensitivity: Test for Shape of Curve









Appendix C Documentation

	Equation	Properties	Units	Documentation	Annotation
Top-Level Model:					
Death_Population[Group_0_to_9](t)	Death_Population[Group_0_to_9](t - dt) + (Death_Rate[Group_0_to_9]) * dt	INIT Death_Population[Group_0_to_9] = 27	People	This stock increases by the inflow to it (death rate) This stock an aggregated stock which is arrayed by the 10 age groups . the researcher initialized this stock value by	

				the number of death people in the year 2020 . Data has been extracted from the Norwegian statistics website : https://www.ssb.no/en Deaths. 2020.Both sexes.Rogaland 0-9 years 5 10-19 years 13 20-29 years 25 30-39 years 41 40-49 years 75 50-59 years 170 60-69 years 342 70-79 years 707 80-89 years 1 003 90 years or older 736 Deaths. 2020 .Both Sexes. Vestland 0-9 years 22 10-19 years 15 20-29 years 31 30-39 years 43 40-49 years 96 50-59 years 198 60-69 years 461 70-79 years 996 80-89 years 1 566 90 years or older 1 338 Each value equals the summing of the number of death population in	

				Rogaland and Vestland, because these two counties forms the West of Norway health region from the year 2020. As Norwegian authorities applied decentralization in health services and merged these two counties in to one health region .	
Death_Population[Group_10_to_19](t)	Death_Population[Group_10_to_19](t - dt) + (Death_Rate[Group_10_to_19]) * dt	INIT Death_Population[Group_10_to_19] = 28			
Death_Population[Group_20_to_29](t)	Death_Population[Group_20_to_29](t - dt) + (Death_Rate[Group_20_to_29]) * dt	INIT Death_Population[Group_20_to_29] = 56			
Death_Population[Group_30_to_39](t)	Death_Population[Group_30_to_39](t - dt) + (Death_Rate[Group_30_to_39]) * dt	INIT Death_Population[Group_30_to_39] = 84			
Death_Population[Group_40_to_49](t)	Death_Population[Group_40_to_49](t - dt) + (Death_Rate[Group_40_to_49]) * dt	INIT Death_Population[Group_40_to_49] = 171			
Death_Population[Group_50_to_59](t)	Death_Population[Group_50_to_59](t - dt) + (Death_Rate[Group_50_to_59]) * dt	INIT Death_Population[Group_50_to_59] = 368			
Death_Population[Group_60_to_69](t)	Death_Population[Group_60_to_69](t - dt) + (Death_Rate[Group_60_to_69]) * dt	INIT Death_Population[Group_60_to_69] = 803			
Death_Population[Group_70_	Death_Population[Group_70_to_79](t - dt) +	INIT Death_Popula			

to_79](t)	(Death_Rate[Group_70_to_79]) * dt	tion[Group_70_to_79] = 1703			
Death_Population[Group_80_to_89](t)	Death_Population[Group_80_to_89](t - dt) + (Death_Rate[Group_80_to_89]) * dt	INIT Death_Population[Group_80_to_89] = 2569			
Death_Population[Group_90_to_100](t)	Death_Population[Group_90_to_100](t - dt) + (Death_Rate[Group_90_to_100]) * dt	INIT Death_Population[Group_90_to_100] = 2074			
Deaths_of_Cancer[Group_0_to_9](t)	Deaths_of_Cancer[Group_0_to_9](t - dt) + (Death_Rate_Of_Cancer[Group_0_to_9]) * dt	INIT Deaths_of_Cancer[Group_0_to_9] = 50	People		
Deaths_of_Cancer[Group_10_to_19](t)	Deaths_of_Cancer[Group_10_to_19](t - dt) + (Death_Rate_Of_Cancer[Group_10_to_19]) * dt	INIT Deaths_of_Cancer[Group_10_to_19] = 100			
Deaths_of_Cancer[Group_20_to_29](t)	Deaths_of_Cancer[Group_20_to_29](t - dt) + (Death_Rate_Of_Cancer[Group_20_to_29]) * dt	INIT Deaths_of_Cancer[Group_20_to_29] = 150			
Deaths_of_Cancer[Group_30_to_39](t)	Deaths_of_Cancer[Group_30_to_39](t - dt) + (Death_Rate_Of_Cancer[Group_30_to_39]) * dt	INIT Deaths_of_Cancer[Group_30_to_39] = 200			
Deaths_of_Cancer[Group_40_to_49](t)	Deaths_of_Cancer[Group_40_to_49](t - dt) + (Death_Rate_Of_Cancer[Group_40_to_49]) * dt	INIT Deaths_of_Cancer[Group_40_to_49] = 500			
Deaths_of_Cancer[Group_50_to_59](t)	Deaths_of_Cancer[Group_50_to_59](t - dt) + (Death_Rate_Of_Cancer[Group_50_to_59]) * dt	INIT Deaths_of_Cancer[Group_50_to_59] = 600			
Deaths_of_Cancer[Group_60_to_69](t)	Deaths_of_Cancer[Group_60_to_69](t - dt) + (Death_Rate_Of_Cancer[Group_60_	INIT Deaths_of_Cancer[Group_6			

	to_69]) * dt	0_to_69] = 700			
Deaths_of_Cancer[Group_70_to_79](t)	Deaths_of_Cancer[Group_70_to_79](t - dt) + (Death_Rate_Of_Cancer[Group_70_to_79]) * dt	INIT Deaths_of_Cancer[Group_70_to_79] = 1500			
Deaths_of_Cancer[Group_80_to_89](t)	Deaths_of_Cancer[Group_80_to_89](t - dt) + (Death_Rate_Of_Cancer[Group_80_to_89]) * dt	INIT Deaths_of_Cancer[Group_80_to_89] = 1700			
Deaths_of_Cancer[Group_90_to_100](t)	Deaths_of_Cancer[Group_90_to_100](t - dt) + (Death_Rate_Of_Cancer[Group_90_to_100]) * dt	INIT Deaths_of_Cancer[Group_90_to_100] = 1000			
Population_Groups[Group_0_to_9](t)	Population_Groups[Group_0_to_9](t - dt) + (Birth_Rate[Group_0_to_9] - Death_Rate[Group_0_to_9] - Being_Older[Group_0_to_9]) * dt	INIT Population_Groups[Group_0_to_9] = 61908+74089	People	The researcher divided Population in to 10 years cohort.So there are to 10 groups of population . Each group of population initialized its value to the number of people in the year 2020 . The reason of dividing age groups in to 10 groups is that we can get the behavior of each group , hence w, we can realize which age groups that are growing more than others, so we can also realize which age group that has more cancer incidents , so the policy makers	

				can initiate policies that be targeted to each age group. Data has been extracted from the Norwegian statistics website : https://www.ssb.no/en Each value equals the summing of the number of population in Rogaland and Vestland, because these two counties forms the West of Norway health region from the year 2020. As Norwegian authorities applied decentralization in health services and merged these two counties in to one health region .	
Population_Groups[Group_10_to_19](t)	Population_Groups[Group_10_to_19](t - dt) + (Birth_Rate[Group_10_to_19] - Death_Rate[Group_10_to_19] - Being_Older[Group_10_to_19]) * dt	INIT Population_Groups[Group_10_to_19] = 62397+78414			
Population_Groups[Group_20_to_29](t)	Population_Groups[Group_20_to_29](t - dt) + (Birth_Rate[Group_20_to_29] - Death_Rate[Group_20_to_29] - Being_Older[Group_20_to_29]) * dt	INIT Population_Groups[Group_20_to_29] = 62589+87788			
Population_Groups[Group_30_to_39](t)	Population_Groups[Group_30_to_39](t - dt) + (Birth_Rate[Group_30_to_39] -	INIT Population_Groups[Group_3			

	Death_Rate[Group_30_to_39] - Being_Older[Group_30_to_39]) * dt	0_to_39] = 68651+86042			
Population_Groups[Group_40_to_49](t)	Population_Groups[Group_40_to_49](t - dt) + (Birth_Rate[Group_40_to_49] - Death_Rate[Group_40_to_49] - Being_Older[Group_40_to_49]) * dt	INIT Population_Groups[Group_40_to_49] = 66138+83158			
Population_Groups[Group_50_to_59](t)	Population_Groups[Group_50_to_59](t - dt) + (Birth_Rate[Group_50_to_59] - Death_Rate[Group_50_to_59] - Being_Older[Group_50_to_59]) * dt	INIT Population_Groups[Group_50_to_59] = 60609+80107			
Population_Groups[Group_60_to_69](t)	Population_Groups[Group_60_to_69](t - dt) + (Birth_Rate[Group_60_to_69] - Death_Rate[Group_60_to_69] - Being_Older[Group_60_to_69]) * dt	INIT Population_Groups[Group_60_to_69] = 47850+67925			
Population_Groups[Group_70_to_79](t)	Population_Groups[Group_70_to_79](t - dt) + (Birth_Rate[Group_70_to_79] - Death_Rate[Group_70_to_79] - Being_Older[Group_70_to_79]) * dt	INIT Population_Groups[Group_70_to_79] = 32497+49969			
Population_Groups[Group_80_to_89](t)	Population_Groups[Group_80_to_89](t - dt) + (Birth_Rate[Group_80_to_89] - Death_Rate[Group_80_to_89] - Being_Older[Group_80_to_89]) * dt	INIT Population_Groups[Group_80_to_89] = 13933+22857			
Population_Groups[Group_90_to_100](t)	Population_Groups[Group_90_to_100](t - dt) + (Birth_Rate[Group_90_to_100] - Death_Rate[Group_90_to_100] - Being_Older[Group_90_to_100]) * dt	INIT Population_Groups[Group_90_to_100] = 3240 +6005			
Population_with_cancer[Group_0_to_9](t)	Population_with_cancer[Group_0_to_9](t - dt) + ("Re-Cancer"[Group_0_to_9] + New_cases_of_cancer_Rate[Group_0_to_9] + Delayed_and_Back_to_System[Group_0_to_9] - Treatment_Process_rate[Group_0_to_9] - Death_Rate_Of_Cancer[Group_0_to_9]) * dt	INIT Population_with_cancer[Group_0_to_9] = 256	People	This stock is an aggregated stock which is arrayed by the age groups which are 10 groups. Each group of population with cancer initialized its value to the number of people who have been cancer diagnose	

				in the period (2016- 2020) The reason for choosing this time of period is that the researcher assumes that population with cancer stock will include people who have cancer not only the first year of the model running , but also those who already have been diagnosed 5 years earlier and they still get treatment at the year 2020. The reason of dividing age groups in to 10 groups is that we can get the behavior of each group , hence w, we can realize which age groups that are growing more than others, so we can also realize which age group that has more cancer incidents , so the policy makers can initiate policies that be targeted to each age group. Data has been extracted from the Norwegian statistics bank https://sb.kreftreg	

				isteret.no/insidens/?lang=en# This stock increases by 2 inflows (new cases of cancer rate , and re-cancer) , and it decreases by 2 outflows which are treatment process rate and death rate of cancer At the end of 2020 there were: 3856 men and women at the age group (0-49) 14108 men and women at the age group(50-69) 18263 men and women at the age group(70+) in west Norway who has cancer diagnose in the period 2016-2020 cancer and they still have cancer . The researcher could not find specific data for each age of the 10 groups that she used in her research , therefore she used these numbers and divided it between each age group regarding	

				to her conceptualization of the problem and from her understanding to the distribution of cancer incidents between age groups . The researcher found also in the Norwegian Institute of Public Health website https://norgeshelsa.no/norgeshelsa/ the same data.	
Population_with_cancer[Group_10_to_19](t)	Population_with_cancer[Group_10_to_19](t - dt) + ("Re-Cancer"[Group_10_to_19] + New_cases_of_cancer_Rate[Group_10_to_19] + Delayed_and_Back_to_System[Group_10_to_19] - Treatment_Process_rate[Group_10_to_19] - Death_Rate_Of_Cancer[Group_10_to_19]) * dt	INIT Population_with_cancer[Group_10_to_19] = 400			
Population_with_cancer[Group_20_to_29](t)	Population_with_cancer[Group_20_to_29](t - dt) + ("Re-Cancer"[Group_20_to_29] + New_cases_of_cancer_Rate[Group_20_to_29] + Delayed_and_Back_to_System[Group_20_to_29] - Treatment_Process_rate[Group_20_to_29] - Death_Rate_Of_Cancer[Group_20_to_29]) * dt	INIT Population_with_cancer[Group_20_to_29] = 700			
Population_with_cancer[Group_30_to_39](t)	Population_with_cancer[Group_30_to_39](t - dt) + ("Re-Cancer"[Group_30_to_39] + New_cases_of_cancer_Rate[Group_30_to_39] + Delayed_and_Back_to_System[Group_30_to_39] -	INIT Population_with_cancer[Group_30_to_39] = 800			

	Treatment_Process_rate[Group_30_to_39] - Death_Rate_Of_Cancer[Group_30_to_39]) * dt				
Population_with_cancer[Group_40_to_49](t)	Population_with_cancer[Group_40_to_49](t - dt) + ("Re-Cancer"[Group_40_to_49] + New_cases_of_cancer_Rate[Group_40_to_49] + Delayed_and_Back_to_System[Group_40_to_49] - Treatment_Process_rate[Group_40_to_49] - Death_Rate_Of_Cancer[Group_40_to_49]) * dt	INIT Population_with_cancer[Group_40_to_49] = 1700			
Population_with_cancer[Group_50_to_59](t)	Population_with_cancer[Group_50_to_59](t - dt) + ("Re-Cancer"[Group_50_to_59] + New_cases_of_cancer_Rate[Group_50_to_59] + Delayed_and_Back_to_System[Group_50_to_59] - Treatment_Process_rate[Group_50_to_59] - Death_Rate_Of_Cancer[Group_50_to_59]) * dt	INIT Population_with_cancer[Group_50_to_59] = 4108			
Population_with_cancer[Group_60_to_69](t)	Population_with_cancer[Group_60_to_69](t - dt) + ("Re-Cancer"[Group_60_to_69] + New_cases_of_cancer_Rate[Group_60_to_69] + Delayed_and_Back_to_System[Group_60_to_69] - Treatment_Process_rate[Group_60_to_69] - Death_Rate_Of_Cancer[Group_60_to_69]) * dt	INIT Population_with_cancer[Group_60_to_69] = 10000			
Population_with_cancer[Group_70_to_79](t)	Population_with_cancer[Group_70_to_79](t - dt) + ("Re-Cancer"[Group_70_to_79] + New_cases_of_cancer_Rate[Group_70_to_79] + Delayed_and_Back_to_System[Group_70_to_79] - Treatment_Process_rate[Group_70_to_79] - Death_Rate_Of_Cancer[Group_70_t	INIT Population_with_cancer[Group_70_to_79] = 12000			

	o_79]) * dt				
Population_with_cancer[Group_80_to_89](t)	Population_with_cancer[Group_80_to_89](t - dt) + ("Re-Cancer"[Group_80_to_89] + New_cases_of_cancer_Rate[Group_80_to_89] + Delayed_and_Back_to_System[Group_80_to_89] - Treatment_Process_rate[Group_80_to_89] - Death_Rate_Of_Cancer[Group_80_to_89]) * dt	INIT Population_with_cancer[Group_80_to_89] = 5000			
Population_with_cancer[Group_90_to_100](t)	Population_with_cancer[Group_90_to_100](t - dt) + ("Re-Cancer"[Group_90_to_100] + New_cases_of_cancer_Rate[Group_90_to_100] + Delayed_and_Back_to_System[Group_90_to_100] - Treatment_Process_rate[Group_90_to_100] - Death_Rate_Of_Cancer[Group_90_to_100]) * dt	INIT Population_with_cancer[Group_90_to_100] = 1263			
Recovered_population[Group_0_to_9](t)	Recovered_population[Group_0_to_9](t - dt) + ("Following-Up_Process_Rate"[Group_0_to_9] - "Re-Cancer"[Group_0_to_9]) * dt	INIT Recovered_population[Group_0_to_9] = 170	People	This stock represents the recovered people who have been totally finished their treatment and controll, and now they considered as recovered population. Those recovered population have been moved from the stock treated and need following-Up through the the outflow following-Up Process rate, which is an inflow to the stock Recovered	

				population. The researcher initialized the value for the arrayed age groups by finding the percent of people who are recovered by the end of year 2020 , then extracted the total number of recovered people, then she initialized the values for each group from her conceptualization and understanding to the different behavior for each group from historical data .	
Recovered_population[Group_10_to_19](t)	Recovered_population[Group_10_to_19](t - dt) + ("Following-Up_Process_Rate"[Group_10_to_19] - "Re-Cancer"[Group_10_to_19]) * dt	INIT Recovered_population[Group_10_to_19] = 250			
Recovered_population[Group_20_to_29](t)	Recovered_population[Group_20_to_29](t - dt) + ("Following-Up_Process_Rate"[Group_20_to_29] - "Re-Cancer"[Group_20_to_29]) * dt	INIT Recovered_population[Group_20_to_29] = 300			
Recovered_population[Group_30_to_39](t)	Recovered_population[Group_30_to_39](t - dt) + ("Following-Up_Process_Rate"[Group_30_to_39] - "Re-Cancer"[Group_30_to_39]) * dt	INIT Recovered_population[Group_30_to_39] = 800			
Recovered_population[Group_40_to_49](t)	Recovered_population[Group_40_to_49](t - dt) + ("Following-Up_Process_Rate"[Group_40_to_49] - "Re-Cancer"[Group_40_to_49]) * dt	INIT Recovered_population[Group_40_to_49] = 1200			
Recovered_population[Group_50_to_59](t)	Recovered_population[Group_50_to_59](t - dt) + ("Following-Up_Process_Rate"[Group_50_to_59]	INIT Recovered_population[Grou			

	- "Re-Cancer"[Group_50_to_59]) * dt	p_50_to_59] = 2000			
Recovered_population[Group_60_to_69](t)	Recovered_population[Group_60_to_69](t - dt) + ("Following-Up_Process_Rate"[Group_60_to_69] - "Re-Cancer"[Group_60_to_69]) * dt	INIT Recovered_population[Group_60_to_69] = 3000			
Recovered_population[Group_70_to_79](t)	Recovered_population[Group_70_to_79](t - dt) + ("Following-Up_Process_Rate"[Group_70_to_79] - "Re-Cancer"[Group_70_to_79]) * dt	INIT Recovered_population[Group_70_to_79] = 3500			
Recovered_population[Group_80_to_89](t)	Recovered_population[Group_80_to_89](t - dt) + ("Following-Up_Process_Rate"[Group_80_to_89] - "Re-Cancer"[Group_80_to_89]) * dt	INIT Recovered_population[Group_80_to_89] = 2500			
Recovered_population[Group_90_to_100](t)	Recovered_population[Group_90_to_100](t - dt) + ("Following-Up_Process_Rate"[Group_90_to_100] - "Re-Cancer"[Group_90_to_100]) * dt	INIT Recovered_population[Group_90_to_100] = 200			
Total_Resources_allocated[Nurses](t)	Total_Resources_allocated[Nurses](t - dt) + (Resources_allocated[Nurses] - Resources_Lost[Nurses]) * dt	INIT Total_Resources_allocated[Nurses] = 1200	People	This stock represents the number of doctors and nurses who are working in cancer treatment department in health Bergen region. These resources are treating cancer patients who get treatment and live in west Norway. https://helse-bergen.no/seksjon-engelsk/seksjon-avdeling/Sider/Cancer-Treatment-and-Medical-	NON-NEGATIVE

				Physics.aspx This stock increases by the inflow resources allocated , which recruit doctors and nurses. This stock decreases by the outflow resources lost which cause a decrease in the stock when doctors and nurses get retired.	
Total_Resources_allocated[Specialized_doctors](t)	Total_Resources_allocated[Specialized_doctors](t - dt) + (Resources_allocated[Specialized_doctors] - Resources_Lost[Specialized_doctors]) * dt	INIT Total_Resources_allocated[Specialized_doctors] = 40			
"Treated_and_Need_Following-Up"[Group_0_to_9](t)	"Treated_and_Need_Following-Up"[Group_0_to_9](t - dt) + (Treatment_Process_rate[Group_0_to_9] - "Following-Up_Process_Rate"[Group_0_to_9] - Delayed_and_Back_to_System[Group_0_to_9]) * dt	INIT "Treated_and_Need_Following-Up"[Group_0_to_9] = 120	People	This stock represents the number of people who were diagnosed with cancer , but they get treated by starting going through the cancer patient pathway system in Norway. Those treated patients have been moved from the stock population with cancer through the the outflow treatment process rate, which is an inflow to the stock treated and need Following-Up. The researcher	

				could not find specific data for this stock , because the Norwegian statistics bank do not differentiate between the two steps(Treatment process and following-up process) . The researcher initialized this stock arrays values by numbers that are less than the initial data for population with cancer , these are the nearest assumed values. This stock decreases by the outflow following -Up process rate .	
"Treated_and_Need_Following-Up"[Group_10_to_19](t)	"Treated_and_Need_Following-Up"[Group_10_to_19](t - dt) + (Treatment_Process_rate[Group_10_to_19] - "Following-Up_Process_Rate"[Group_10_to_19] - Delayed_and_Back_to_System[Group_10_to_19]) * dt	INIT "Treated_and_Need_Following-Up"[Group_10_to_19] = 180			
"Treated_and_Need_Following-Up"[Group_20_to_29](t)	"Treated_and_Need_Following-Up"[Group_20_to_29](t - dt) + (Treatment_Process_rate[Group_20_to_29] - "Following-Up_Process_Rate"[Group_20_to_29] - Delayed_and_Back_to_System[Group_20_to_29]) * dt	INIT "Treated_and_Need_Following-Up"[Group_20_to_29] = 250			
"Treated_and_Need_Following-Up"[Group_30	"Treated_and_Need_Following-Up"[Group_30_to_39](t - dt) + (Treatment_Process_rate[Group_30_to_39] - "Following-	INIT "Treated_and_Need_Following-			

_to_39](t)	Up_Process_Rate"[Group_30_to_39] - Delayed_and_Back_to_System[Group_30_to_39]) * dt	Up"[Group_30_to_39] = 300			
"Treated_and_Need_Following-Up"[Group_40_to_49](t)	"Treated_and_Need_Following-Up"[Group_40_to_49](t - dt) + (Treatment_Process_rate[Group_40_to_49] - "Following-Up_Process_Rate"[Group_40_to_49] - Delayed_and_Back_to_System[Group_40_to_49]) * dt	INIT "Treated_and_Need_Following-Up"[Group_40_to_49] = 350			
"Treated_and_Need_Following-Up"[Group_50_to_59](t)	"Treated_and_Need_Following-Up"[Group_50_to_59](t - dt) + (Treatment_Process_rate[Group_50_to_59] - "Following-Up_Process_Rate"[Group_50_to_59] - Delayed_and_Back_to_System[Group_50_to_59]) * dt	INIT "Treated_and_Need_Following-Up"[Group_50_to_59] = 450			
"Treated_and_Need_Following-Up"[Group_60_to_69](t)	"Treated_and_Need_Following-Up"[Group_60_to_69](t - dt) + (Treatment_Process_rate[Group_60_to_69] - "Following-Up_Process_Rate"[Group_60_to_69] - Delayed_and_Back_to_System[Group_60_to_69]) * dt	INIT "Treated_and_Need_Following-Up"[Group_60_to_69] = 600			
"Treated_and_Need_Following-Up"[Group_70_to_79](t)	"Treated_and_Need_Following-Up"[Group_70_to_79](t - dt) + (Treatment_Process_rate[Group_70_to_79] - "Following-Up_Process_Rate"[Group_70_to_79] - Delayed_and_Back_to_System[Group_70_to_79]) * dt	INIT "Treated_and_Need_Following-Up"[Group_70_to_79] = 1500			
"Treated_and_Need_Following-Up"[Group_80_to_89](t)	"Treated_and_Need_Following-Up"[Group_80_to_89](t - dt) + (Treatment_Process_rate[Group_80_to_89] - "Following-Up_Process_Rate"[Group_80_to_89] - Delayed_and_Back_to_System[Group_80_to_89]) * dt	INIT "Treated_and_Need_Following-Up"[Group_80_to_89] = 300			
"Treated_and_Need_Following-	"Treated_and_Need_Following-Up"[Group_90_to_100](t - dt) + (Treatment_Process_rate[Group_90_	INIT "Treated_and_Need_Followi			

Up"[Group_90_to_100](t)	to_100] - "Following-Up_Process_Rate"[Group_90_to_100] - Delayed_and_Back_to_System[Group_90_to_100]) * dt	ng-Up"[Group_90_to_100] = 150			
Being_Older[Group_0_to_9]	Population_Groups[Group_0_to_9]/ Time_Staying_in_One_Age_Group		People/Years	This outflow represents the rate of people per year that will become older .This is an integrated outflow , that is arrayed by the age groups of population which are 10 groups The researcher divided population groups in to 10 cohort, therefore to calculate the rate of transfer to the next age group , we need to have 10 outflows.these outflows are aggregated in to this aggregated outflow. All groups have the same equation except the last age group (90-100) , because this age group assumed not to be older. The equation used in this outflow includes: population groups(For each population) / Time staying in one age group	UNIFLOW

				(that is 10 Years) This equation shows an outflow equation with the stock that is divided by the delay time of 10 years.	
Being_Older[Group_10_to_19]	Population_Groups[Group_10_to_19]/Time_Staying_in_One_Age_Group				
Being_Older[Group_20_to_29]	Population_Groups[Group_20_to_29]/Time_Staying_in_One_Age_Group				
Being_Older[Group_30_to_39]	Population_Groups[Group_30_to_39]/Time_Staying_in_One_Age_Group				
Being_Older[Group_40_to_49]	Population_Groups[Group_40_to_49]/Time_Staying_in_One_Age_Group				
Being_Older[Group_50_to_59]	Population_Groups[Group_50_to_59]/Time_Staying_in_One_Age_Group				
Being_Older[Group_60_to_69]	Population_Groups[Group_60_to_69]/Time_Staying_in_One_Age_Group				
Being_Older[Group_70_to_79]	Population_Groups[Group_70_to_79]/Time_Staying_in_One_Age_Group				
Being_Older[Group_80_to_89]	Population_Groups[Group_80_to_89]/Time_Staying_in_One_Age_Group				
Being_Older[Group_90_to_100]	0				
Birth_Rate[Group_0_to_9]	expected_Birth_Rate_Fraction*Total_Population_West_Norway_Region		People/Years	This inflow increases the stock population groups.This inflow shows how many people per year are growing. This inflow is an aggregated	UNIFLOW

				inflow which is arrayed by the age groups. the equation for birth rate will be the same for all age groups except the age group (0-9) years old . The equation for other age groups is coming from the outflow being older.while the equation for the age group (0-9) is the total population*birth rate fraction). Birth rate for the youngest group gives us more realistic results.	
Birth_Rate[Group_10_to_19]	Being_Older[Group_0_to_9]				
Birth_Rate[Group_20_to_29]	Being_Older[Group_10_to_19]				
Birth_Rate[Group_30_to_39]	Being_Older[Group_20_to_29]				
Birth_Rate[Group_40_to_49]	Being_Older[Group_30_to_39]				
Birth_Rate[Group_50_to_59]	Being_Older[Group_40_to_49]				
Birth_Rate[Group_60_to_69]	Being_Older[Group_50_to_59]				
Birth_Rate[Group_70_to_79]	Being_Older[Group_60_to_69]				
Birth_Rate[Group_80_to_89]	Being_Older[Group_70_to_79]				
Birth_Rate[Group_90_to_100]	Being_Older[Group_90_to_100]				
Death_Rate[Age_Groups]	Population_Groups/Expected_Life_Expectancy		People/	This outflow decreases the	UNIFLOW

			Years	stock population groups.This outflow shows how many people die per year. This outflow is an aggregated outflow which is arrayed by the age groups. Using arrayed outflow gives a detailed result about death rate for each group , so we can check the death rate for each age group and found out which age groups that have more life expectancy, hence , that helps decision makers to know which age groups that are threaten more than other age groups. The equation for death rate is the same for all aggregated age groups . The equation for death rate outflow is the result of : population groups *death rate fraction.	
Death_Rate_Of_Cancer[Age_Groups]	Population_with_cancer*"Expected_Fraction-Deaths_Of_Caner"		People/years		UNIFLOW
Delayed_and_	"Treated_and_Need_Following-		Peo		

Back_to_System[Age_Groups]	Up"*Back_To_System_Fraction		ple/years		
"Following-Up_Process_Rate"[Age_Groups]	("Treated_and_Need_Following-Up"*"Following-Up_Fraction")		People/years		
New_cases_of_cancer_Rate[Age_Groups]	Population_Groups*"Expected_Fraction-_New_Cancer_Cases"		People/Years	This inflow causes an increase in the stock (new cases of cancer). This inflow shows how many new incidents of cancer are transferred to the stock population with cancer . the equation of this inflow is the product of population groups by the fraction of new cases of cancer. This inflow is an integrated flow that is arrayed by the age groups of population. Using arrayed inflow gives a detailed result about the new cases of cancer rate for each group , so we can check that rate for each age group and found out which age groups that are exposed to get cancer , hence , that helps decision makers	UNIF LOW

				to know which age groups that are threaten more than other age groups. The equation this inflow is the same for all aggregated age groups., but the fraction differs. The equation for this inflow is the result of : population groups*fraction of new cases of cancer	
"Re-Cancer"[Age_Groups]	"Re-cancer_Fraction"*Recovered_population		People/Years	This is an outflow from the stock recovered population, so it causes an increase to this stock.And it is also an inflow to the stock population with cancer , so this stock increases by the inflow re-cancer. This flow is a product of the the stock recovered population and and the re-cancer fraction	
Resources_allocated[Health_Personnel]	IF Policy_2= 0 THEN (Total_Resources_allocated*Resources_allocation_Fraction) ELSE ((Total_Resources_allocated+(Total_Resources_allocated*.25))*Resources_allocation_Fraction)		People/Years		
Resources_Lost[Health_Personnel]	Total_Resources_allocated*Average_Resource_Lose_Fraction		People/Years	This outflow represents the rate of nurses and doctors who get	

				retired after a period of working time. This rate is affected by the resources loss fraction. when there is a high loss fraction , that means there will be less resources in the stock total resources allocated and vice versa.	
Treatment_Process_rate[Age_Groups]	(Population_with_cancer*Treatment_Fraction)		People/years	This flow represents the treatment process rate. This is an outflow that decreases the level of stock population with cancer , and also its an inflow that increases the level of people who are treated and needed following-up. That means when this flow rate is high , there will be less people who are diagnosed with cancer and there will be more people who are treated and need following up, and vice versa.	UNIF LOW
"Average_Following-Up_Fraction"	IF TIME >= 2040 THEN (IF Policy_2=1 THEN 0.5 ELSE 0.4 AND IF Policy_1 = 1 THEN 0.2 ELSE 0.4) ELSE 0.4		dmnl/years		
Average_Fract	IF Shock_Function =1 THEN .02		dm		

ion_of_Resources_allocation	ELSE .04 {.04		nl/years		
Average_Fraction_of_Resources_Lose	IF Shock_Function=1 THEN .06 ELSE .03 {.06		dmnl/years		
Average_Resource_Lose_Fraction	SMTH1(Average_Fraction_of_Resources_Lose, Time_To_adopt_Reallocation_Policy)		dmnl/years	This converter	DELAY CONVERTER
Average_Treatment_Fraction	IF TIME >=2040 THEN (IF Policy_1 =1 THEN 0.8 ELSE 0.5 AND IF Policy_2 =1 THEN 0.6 ELSE 0.5) ELSE 0.5		dmnl/years	Average Treatment fraction during the second phase is 0.3 dml/ years. This average treatment fraction means that in average , there will be a fraction of 0.5 of patients will be treated .By other words, in average there will be a fraction of 0.5 patients per year that will be transferred from the stock population with cancer to the stock treated and need following-Up. Using the equation if her, means that if we will not apply any of the policies , the average treatment fraction will be .05 dml/ years . But when we apply any of the policies, that means that there will be more	

				people who will be treated , because policy two will add more health personnel, and that is assumed will decrease the average delay time in following-up patients , and the first policy will allocate more health personnel in the treatment process. So if any of these policies will be adapted , the average treatment fraction is considered to increase to 0.7 in average .	
Back_To_System_Fraction	IF Shock_Function=1 THEN .3 ELSE .1 {.3		dmnl/years		
End_of_Shock	2045		years	This converter represents the time at which the shock condition will end in the system . Choosing the year 2045 as the end time of the shock has been chosen randomly, and we can change it to test the system during different time to start. But the reason that the researcher preferred to use this time is that becomes in the	

				middle of the simulation period , that give us the chance to see how the system will perform before and after the shock.	
expected_Birth_Rate_Fraction	GRAPH(TIME) Points: (2020.00, 0.021), (2022.63157895, 0.020977265947), (2025.26315789, 0.0209492046794), (2027.89473684, 0.0209145678842), (2030.52631579, 0.0208718147341), (2033.15789474, 0.0208190433437), (2035.78947368, 0.0207539061635), (2038.42105263, 0.0206735055484), (2041.05263158, 0.0205742648554), (2043.68421053, 0.0204517693354), (2046.31578947, 0.0203005697421), (2048.94736842, 0.0201139399208), (2051.57894737, 0.0198835775935), (2054.21052632, 0.0195992350299), (2056.84210526, 0.0192482631743), (2059.47368421, 0.0188150489488), (2062.10526316, 0.0182803207016), (2064.73684211, 0.0176202909024), (2067.36842105, 0.0168055979472), (2070.00, 0.0158)		dmnl/years	This converter includes the birth rate fraction of total population (Population groups). Population who grow by this birth rate fraction are the group of (0-9) years old. This age group is the group of people who are assumed to grow by the birth rate fraction, while other population groups grow by transferring from age group to the other , by using the outflow (being older) and the delay time of 10 years, except the age group of (90-100) which is assumed to to die after that and be transferred to death stock through the death rate outflow. The researcher used graphical function to reveal the expected birth	GF EXTRAPOLATED

				rate fraction by using the minimum and maximum birth rate fractions that has been found in the Statistics Norway https://www.ssb.no/en Statistics Norway publishes three alternatives of projections for expected birth rate Fraction which are: High alternative (HHH)and main/medium alternative (MMM)and low alternative(LLL). The researcher chooses to use MMM (Medium alternative, which assumes the medium level for each component, because this is what is assumed to be most plausible. The same data has been also found in : https://www.macrotrends.net/countries/NOR/norway/birth-rate	
"Expected_Fraction-_New_Cancer_Cases"	GRAPH(TIME) Points: (2020.00, 0.035), (2021.66666667, 0.0352958924981), (2023.33333333, 0.0356018143061), (2025.00, 0.0359181053684), (2026.66666667, 0.0362451171522), (2028.33333333, 0.0365832130375), (2030.00,		dmnl/years	https://www.kreftregisteret.no/en/Temasider/key-figures-on-cancer/	

	0.0369327687213), (2031.66666667, 0.0372941726346), (2033.33333333, 0.0376678263746), (2035.00, 0.0380541451505), (2036.66666667, 0.0384535582452), (2038.33333333, 0.0388665094921), (2040.00, 0.0392934577684), (2041.66666667, 0.0397348775049), (2043.33333333, 0.0401912592135), (2045.00, 0.040663110032), (2046.66666667, 0.0411509542875), (2048.33333333, 0.0416553340794), (2050.00, 0.0421768098816), (2051.66666667, 0.0427159611653), (2053.33333333, 0.043273387043), (2055.00, 0.0438497069341), (2056.66666667, 0.0444455612533), (2058.33333333, 0.0450616121223), (2060.00, 0.0456985441055), (2061.66666667, 0.0463570649705), (2063.33333333, 0.047037906475), (2065.00, 0.0477418251795), (2066.66666667, 0.0484696032885), (2068.33333333, 0.049222049519), (2070.00, 0.05)			At the end of 2020 there were: 3856 men and women at the age group (0-49) 14108 men and women at the age group(50-69) 18263 men and women at the age group(70+) in west Norway who has cancer diagnose in the period 2016-2020 cancer and they still have cancer . So the fraction of new cases of cancer at the end of 2020 can be calculated : Total Population of West Norway/ Total New cases of cancer = 1047000/36227= 0.035 The researcher could not find specific data for each age of the 10 groups that she used in her research , therefore she used this fraction and created this graphical Function , to expect the future fraction of new cases of cancer.Based on historical datat, the fraction of	

				new cases is increasing over time , so , the maximum value that found in data is .04. The researcher found also in the Norwegian Institute of Public Health website https://norgeshelsa.no/norgeshelsa/ the same data.	
"Expected_Fraction-Deaths_Of_Caner"	GRAPH(TIME) Points: (2020.00, 0.0026), (2021.66666667, 0.00260789046662), (2023.33333333, 0.00261604838149), (2025.00, 0.00262448280982), (2026.66666667, 0.00263320312406), (2028.33333333, 0.00264221901433), (2030.00, 0.00265154049923), (2031.66666667, 0.00266117793692), (2033.33333333, 0.00267114203666), (2035.00, 0.00268144387068), (2036.66666667, 0.00269209488654), (2038.33333333, 0.00270310691979), (2040.00, 0.00271449220716), (2041.66666667, 0.00272626340013), (2043.33333333, 0.00273843357903), (2045.00, 0.00275101626752), (2046.66666667, 0.00276402544767), (2048.33333333, 0.00277747557545), (2050.00, 0.00279138159684), (2051.66666667, 0.00280575896441), (2053.33333333, 0.00282062365448), (2055.00,		dmnl/years	More than 11.000 Norwegians died of cancer in 2019. (https://www.kreftregisteret.no/en/Temasider/key-figures-on-cancer/) The researcher could not find specific data for each deaths in each health region , therefore she used this fraction and divided it between the four health regions regarding to her conceptualization of the problem and from her understanding to the distribution of cancer incidents between health regions and age groups . The researcher found also in the Norwegian	

	0.00283599218491), (2056.66666667, 0.00285188163342), (2058.33333333, 0.0028683096566), (2060.00, 0.00288529450948), (2061.66666667, 0.00290285506588), (2063.33333333, 0.00292101083933), (2065.00, 0.00293978200479), (2066.66666667, 0.00295918942103), (2068.33333333, 0.00297925465384), (2070.00, 0.003)			Institute of Public Health website https://norgeshelsa.no/norgeshelsa/ the same data. The researcher divided the total number of death people by 4 to get this number for each region 2750.Then Death of cancer rate fraction can be calculated by dividing the number of died people of cancer in Health region west by the Total people in West Norway :: died people per year/Total population West Norway= 2750/1047000= 0.0026 From Historical data, the researcher conceptualized that deaths of cancer increases over time, so she created this graphical function with ,inimum value calculated and the maximum value expected by data which is 0.003.	
Expected_Life_Expectancy	GRAPH(TIME) Points: (2020.00, 82.000), (2021.72413793,		years	The researcher used graphical	

	82.9187154737), (2023.44827586, 83.7190625154), (2025.17241379, 84.4162918595), (2026.89655172, 85.023689317), (2028.62068966, 85.5528289388), (2030.34482759, 86.0137935606), (2032.06896552, 86.4153669334), (2033.79310345, 86.7652010987), (2035.51724138, 87.0699621997), (2037.24137931, 87.3354575055), (2038.96551724, 87.5667460694), (2040.68965517, 87.7682351302), (2042.4137931, 87.9437640925), (2044.13793103, 88.0966776872), (2045.86206897, 88.2298897063), (2047.5862069, 88.345938525), (2049.31034483, 88.447035471), (2051.03448276, 88.5351069622), (2052.75862069, 88.611831214), (2054.48275862, 88.6786702189), (2056.20689655, 88.7368976041), (2057.93103448, 88.7876229014), (2059.65517241, 88.8318126889), (2061.37931034, 88.8703090099), (2063.10344828, 88.9038454175), (2064.82758621, 88.9330609531), (2066.55172414, 88.9585123231), (2068.27586207, 88.9806845073), (2070.00, 89.000)			function to reveal the expected Life expectancy by using the minimum and maximum values for Life Expectancy that has been found in the Statistics Norway https://www.ssb.no/en Statistics Norway publishes three alternatives of projections for expected Life Expectancy which are: High alternative (HHH)and main/medium alternative (MMM)and low alternative(LLL). The researcher chooses to use MMM (Medium alternative, which assumes the medium level for each component, because this is what is assumed to be most plausible. The same data has been also found in : https://www.macrotrends.net/countries/NOR/norway/life-expectancy	
"Expected_Total_population(DATA)"	GRAPH(TIME) Points: (2020.00, 1116423.0), (2021.00, 1120066.0), (2022.00, 1124056.0), (2023.00, 1128603.0), (2024.00, 1133224.0),		years		

	(2025.00, 1138012.0), (2026.00, 1143039.0), (2027.00, 1148009.0), (2028.00, 1152937.0), (2029.00, 1157822.0), (2030.00, 1162645.0), (2031.00, 1167407.0), (2032.00, 1172073.0), (2033.00, 1176649.0), (2034.00, 1181158.0), (2035.00, 1185612.0), (2036.00, 1190004.0), (2037.00, 1194269.0), (2038.00, 1198336.0), (2039.00, 1202202.0), (2040.00, 1205875.0), (2041.00, 1209359.0), (2042.00, 1212644.0), (2043.00, 1215728.0), (2044.00, 1218621.0), (2045.00, 1221323.0), (2046.00, 1223825.0), (2047.00, 1226128.0), (2048.00, 1228240.0), (2049.00, 1230145.0), (2050.00, 1231870.0)				
"Following-Up_Fraction"	SMTH1("Average_Following-Up_Fraction", "Time_to_adopt_to_Following-Up_Policy")		dmnl/years	This converter represents the delay fraction that is needed to control and follow-up treated people who are assumed to be passed the dangerous stage of the disease . Regarding helsenorge.no the cancer patient pathway system that is used in Norway (this type of following-up is part of the patient pathway system that the Norwegian ministry of health introduced in its cancer care system in January 2015) there are 3 phases to treat people.	DELAY CONVERTER

				Helsenorge.no. (2020). Cancer patient pathways. Retrieved from https://www.helsenorge.no/en/sykdom/kreft/cancer-patient-pathways/#pathway-times-in-the-cancer-patient-pathway Møller, Bjørn. (2021). Cancer patient pathways in Norway. The researcher used in this delay converter SMTH1 equation that indicates only the third phase of treatment which she called (following-up process , to differentiate between the 3 phases of treatment) , while the first phase is considered as diagnosing of the case and that is considered to be before treatment , and the second phase is condidered during the treatment process. The purpose of using SMTH1 equation is that	

				there is adelay in controlling patients, that delay is affected by the fraction of people that needs control and the delay time to control them. Average delay time during third phase is 4 years. This delay time means that in average , each patient needs 4 years to be controlled after treatment , that includes many appointments scheduled and all needed surgeries or checks-up after the main treatment phase .By other words, it takes 4 years to transfer a patient from the stock treated and need following-Up, to the stock recovered population. This converter could be named also following-Up time or Control needed time. But the researcher used the name delay time as this name is compatible with system dynamics models	

				Using the equation if her, means that if there is another delay that caused by external conditions like pandemics as in Covid-19 , the shock means that there will be more delay in following-Up process .	
"Following-Up_Resources"	(Total_Resources_allocated[Specialized_doctors]+Total_Resources_allocated[Nurses])*"Fraction_Of_following-Up_Resources"		People		
"Fraction_Of_following-Up_Resources"	IF Policy_1 =1 THEN 0.1 ELSE 0.5		dmnl		
Fraction_Of_Treatment_Resources	1-"Fraction_Of_following-Up_Resources"		dmnl		
Fractions_Of_Resources	0		dmnl		
Key_Performance_Indicators	0		dmnl		
"Patients_Followed-Up_by_Current_Resources"	"Following-Up_Resources"*5		People	This converter represents how many patients are considered as the capacity that all specialized doctors can treat . The researcher assumed that each doctor can treat 4 patients . So the equation for this converter= total specialized doctors*4 We need this	

				converter to be able to calculate the gap between actual need for specialized doctors and the current capacity	
Patients_Treated_by_current_Resources	Treatment_Resources*3		People	This converter represents how many patients are considered as the capacity that all nurses can treat . The researcher assumed that each nurse can hep 4 patients . So the equation for this converter= total nurses*4 We need this converter to be able to calculate the gap between actual treated patients by nurses and the current capacity for nurses	
Policy_1	IF Shock_Key=0 THEN Policy_1_Key ELSE (IF Shock_Function<>0 THEN Policy_1_Key ELSE 0)		dmnl	This converter depicts the conditions that will be in the system during the first policy. Using If equation gives the user of the model the flexibility to choose either to use the policy 1 during the shock or without the shock. When there is a shock condition like for example	

				covid-19 or any pandemics that have a negative effect on the system , we can apply this policy . we can test the effect of policy on variables behaviors either during the shock or without the shock .This is the main purpose of using if equation and also the sighn <> which means not equal . This equations says: If the shock key is not active, so the policy 2 key will be active. And when the shock function will not equal zero that means this converter will equal to policy 2 key.If the shock Function equals zero that means this converter will be zero. Policy 2 converter has been designed to help in determining which value will be used in the following-Up delay time converter and the average following-Up fraction	

				converter.	
Policy_1_Key	0		dmnl	This key is used to switch policy 1 of and on. when we want to use the first policy , we have to use in this converter the value one . when we do not want to use the first Policy , we have to use in this converter the value Zero.	
Policy_2	IF Shock_Key=0 THEN Policy_2_Key ELSE (IF Shock_Function<>0 THEN Policy_2_Key ELSE 0)		dmnl	This converter depicts the conditions that will be in the system during first policy. Using If equation gives the user of the model the flexibility to choose either to use the policy 1 during the shock or without the shock. When there is a shock condition like for example covid-19 or any pandemics that have a negative effect on the system , we can apply this policy . we can test the effect of policy on variables behaviors either during the shock or without the shock .This is the main purpose of using if equation	

				and also the sign <> which means not equal . This equations says: If the shock Function is not active, so the policy 2 key will be active. And when the shock function will not equal zero that means this converter will equal to policy 2 key.If the shock key equals zero that means this converter will be zero. Policy 2 converter has been designed to help in determining which value will be used in the following-Up delay time converter and the average following-Up fraction converter.	
Policy_2_Key	0		dmnl	This key is used to switch the second policy of and on. when we want to use the second policy , we have to use in this converter the value one . when we do not want to use the second Policy , we have to use in this converter the value Zero.	

Policy_Keys	0		dmnl		
Pressure_On_Cancer_Healthcare_system	Pressure_On_Treatment_Resources/"Pressure_On_Following-Up_Resources"		dmnl	This converter depicts to which extend the health sector is exposed to pressure.We can measure if the health system able to treat people efficiently or not. The higher result of this equation means that there is a higher pressure on health system , because the treatment process is the main stage in cancer medication stages.The following-Up stage is more flexible and patients can be followed-up or controlled by different ways, therefore the researcher created this converter with this equation.The purpose of this equation is to measure and find out how the result of this equation will change when we change policies.The policy that gives less value (Pressure) is better than the	

				policy that gives higher value.	
"Pressure_On_ Following- Up_Resources "	"Total_treated_and_Need_Following -Up"/"Patients_Followed- Up_by_Current_Resources"		dm nl	This converter depicts to which extend the following-Up process or the following-Up resource is exposed to pressure.We can measure if the following-Up resource is able to monitor people efficiently or not. But from the conceptualization of the following- Up process , the researcher assumes that this pressure will not affect the system negatively because of the flexibility and ability of following-up patients by different ways other than admitting the hospital. The less pressure on following-Up resources is a good indicator , but when it is compared by the pressure on treatment resources, we have to prioritize to get less pressure on treatment resources than the pressure on	

				following-up resources. This equation finds out the percentage of cancer patients that the current resources is able to monitor and control them, so they are not in emergence situation as those who need treatment to do tumor excision for example. The purpose of this equation is mainly to calculate the pressure on the whole health system. If the result of this equation = 1 that means the number of people who needs to be followed-up= the capacity of resources available to follow them up. If the result of this equation> 1 that means the number of people who need following-Up is higher than the capacity of resources available. In real world , it is not easy to achieve the result of this equation	

				to be 1 ,because of the delays in systems.these delays that are in the form of waiting and hiring health personnel, etc. But the result of this equation could be used as an indicator to evaluate the pressure on following-Up resources. The higher result of this equation means that there is a higher pressure on following-Up resources.The purpose of this equation is to measure and find out how the result of this equation will change when we change policies.By assuming that following-Up process needs less resources because of its flexibility and non emergency in patients cases, we can assume that the policy that gives higher value (Pressure) is better than the policy that gives lower value.That assumption is only valid when	

				the other key performance indicators shows positive results in comparison to the same result for other policies .	
Pressure_On_Treatment_Resources	Total_Population_With_Cancer/Patients_Treated_by_current_Resources		dmnl	This converter depicts to which extend the treatment process or treatment resource is exposed to pressure.We can measure if the treatment resource is able to treat people efficiently or not. This equation finds out the percentage of cancer patients that the current resources is able to treat them . If the result of this equation = 1 that means the number of people who needs treatment = the capacity of resources available to treat them If the result of this equation> 1 that means the number of people who need treatment is higher than the capacity of resources available to treat them. In real world , it	

				is not easy to achieve the result of this equation to be 1 ,because of the delays in systems.these delays that are in the form of waiting and hiring health personnel, etc. But the result of this equation could be used as an indicator to evaluate the pressure on treatment resources. The higher result of this equation means that there is a higher pressure on treatment resources , because the treatment process is the main stage in cancer medication stages.The purpose of this equation is to measure and find out how the result of this equation will change when we change policies.The policy that gives less value (Pressure) is better than the policy that gives higher value.	
"Re-cancer_Fractio	.05 {RANDOM(.007, .009)		dm nl/y	This converter	

n"			ears	represents the fraction of people who has been recovered , but they get cancer again , so they come back to the stock population with cancer. https://www.kreftregisteret.no/en/Temasider/key-figures-on-cancer/	
Resources_allocation_Fraction	SMTH1(Average_Fraction_of_Resources_allocation, Time_To_adopt_Reallocation_Policy)		dmnl/years		DELAY CONVERTER
Shock_Function	IF Shock_Key=1 THEN STEP(1, Start_of_Shock)+STEP(-1, End_of_Shock) ELSE 0		dmnl	This converter represents the case in which there is an emergency situation(Like a pandemic as in Covid-19) that happens and that causes delay in treatment process. When this key have the value 0 , that means there is no emergency situation, and this key is not active. When this key has the value 1, that means there is an emergency situation and this key is active.	
Shock_Key	0		dmnl	This key is used to switch the shock condition off and on. when	

				we want to test the system during a shock , we have to use in this converter the value one . when we there is no shock condition , we have to use in this converter the value Zero.	
"Shock-_Key"	0		dm nl		
Start_of_Shoc k	2040		yea rs	This converter represents the time at which the shock condition will start in the system . Choosing the year 2040 as the start time of the shock has been chosen randomly, and we can change it to test the system during different time to start. But the reason that the researcher preferred to use this time is that becomes in the middle of the simulation period , that give us the chance to see how the system will perform before and after the shock.	
Time_Staying_ in_One_Age_ Group	10		yea rs	This variable represents the delay time that each age group after the year of 9 takes to go to	

				another age group . We divided age groups in to 10 years cohort, therefore delay time to step to the other page group is 10 years.	
Time_To_adopt_Reallocation_Policy	IF Shock_Function= 0 THEN 1 ELSE 5		years		
"Time_to_adopt_to_Following-Up_Policy"	IF Policy_1 OR Policy_2 =1 THEN 1 ELSE 5		years	following-Up Average delay time during third phase is 4 years. This delay time means that in average , each patient needs 4 years to be controlled after treatment , that includes many appointments scheduled and all needed surgeries or checks-up after the main treatment phase .By other words, it takes in average 4 years to transfer a patient from the stock treated and need following-Up, to the stock recovered population. Using the equation if her, means that if we will not apply policy two , the average delay time will be 7 years . But when	

				we apply policy 2 that means that there will be less delay in following-Up process, because policy two will add more health personnel, and that is assumed will decrease the average delay time in following-up patients , which is considered to be reduced to 4 Years in average .	
Time_to_adopt _to_Treatment _Policy	IF Policy_1 OR Policy_2=1 THEN 1 ELSE 5		yea rs	Average Treatment delay time during the second phase is 6 years. This delay time means that in average , each patient needs 6 to be treated , that includes many appointments scheduled and all needed surgeries or checks-up after being diagnosed as a cancer patient in the first phase .By other words, it takes in average 6 years to transfer a patient from the stock population with cancer to the stock treated and need following-Up. Using the	

				equation if her, means that if we will not apply any of the policies , the average delay time will be 6 years . But when we apply any of the policies, that means that there will be less delay in treatment process, because policy two will add more health personnel, and that is assumed will decrease the average delay time in following-up patients , and policy one will allocate more health personnel in the treatment process. so if any of these policies will be adapted , the average delay time in treatment is considered to be reduced to 3 Years in average .	
Total_Death_Population	SUM(Death_Population)		People	This variable represents the total death population, which is the summing of all death population in the 10 age population groups. The purpose of this variable is to give the reader a	

				summarized view of the death population behavior.While to get more detailed view , the reader can check the stock death population , that shows the deaths for each age group.	
Total_Deaths_Of_Cancer	SUM(Deaths_of_Cancer)		People	This variable represents the total death population of cancer , which is the summing of all death population of cancer in the 10 age population groups. The purpose of this variable is to give the reader a summarized view of the death population of cancer behavior.While to get more detailed view , the reader can check the stock deaths of cancer , that shows the deaths of cancer for each age group.	
Total_New_Cases_Of_Cancer_Rate	SUM(New_cases_of_cancer_Rate)		People/years		
Total_Population_West_Norway_Region	SUM(Population_Groups[*])		People	This summing converter includes the total population ,	SUMMING CON

				which equals all population groups in addition to Migrations . Using this variable is useful when we need to show the behavior of total population regardless dividing people in to age groups.	VERTER
Total_Population_With_Cancer	SUM(Population_with_cancer)		People		
Total_Recovered	SUM(Recovered_population)		People	This variable represents the total recovered people who have been totally finished their treatment and controll, and now they considered as recovered population. This variable is the summing of all recovered population population in the 10 age population groups that are arrayed in the stock recovered population . The purpose of this variable is to give the reader a summarized view of the stock recovered population behavior.To get more detailed view , the reader	

				can check that stock which shows the behavior for each age group.	
Total_Resources	SUM(Total_Resources_allocated)		People	This converter represents the total number of resources(nurses and doctors). This value have the same value as the stock (total resources allocated) , but the researcher used this converter to be able to se the behavior of the total resources as the stock of resources is an integrated stock for doctors and nurses. This converter shows the reader the general behavior for the resources, and to get a detailed curves about nurses and doctors, the reader can check the integrated stock behavior .	
"Total_treated_and_Need_Following-Up"	SUM("Treated_and_Need_Following-Up")		People	This variable represents the total treated people who need following up and control and they are moving to the next stock in the model (Recovered	

				population) through the outflow following-Up process rate. This variable is the summing of all treated and needed following -up population in the 10 age population groups. The purpose of this variable is to give the reader a summarized view of the stock treated and need following-Up behavior.To get more detailed view , the reader can check that stock which shows the behavior for each age group.	
Treatment_Fraction	SMTH1(Average_Treatment_Fraction, Time_to_adopt_to_Treatment_Policy)		dmnl/years	This converter represents the delay time that is needed to treat population with cancer . Regarding helsenorge.no the cancer patient pathway system that is used in Norway (this type of treatment is part of the patient pathway system that the Norwegian ministry of health introduced in its cancer care system in January	DELAY CONVERTER

				2015) there are 3 phases to treat people. Helsenorge.no. (2020). Cancer patient pathways. Retrieved from https://www.helsenorge.no/en/sykdom/kreft/cancer-patient-pathways/#pathway-times-in-the-cancer-patient-pathway Møller, Bjørn. (2021). Cancer patient pathways in Norway. The researcher used in this converter the average delay time that indicates only the second phase of treatment , while the first phase is considered as diagnosing of the case and that is considered to be before treatment , and the third delay time is considered to be during the following-up process. Average delay time during second phase is 3 years. This delay time means that in	

				average , each patient needs 3 years to be treated , that includes many appointments scheduled and all needed surgeries.By other words, it takes 3 years to transfer a patient from the stock patients with cancer, to the stock treated and needed following-Up. This converter could be named also treatment time/ treatment needed time. But the researcher used the name delay time as this name is compatible with system dynamics models. Using the equation if her, means that if there is another delay that caused by external conditions like pandemics as in Covid-19 , the shock means that there will be more delay in treatment .	
Treatment_Resources	(Total_Resources_allocated[Nurses] +Total_Resources_allocated[Specialized_doctors])*Fraction_Of_Treatment_Resources		People		

Total	Count	Including Array Elements
Variables	66	204
Sectors	5	
Stocks	7	62
Flows	11	94
Converters	48	48
Constants	11	11
Equations	48	131
Graphicals	5	5
Macro Variables	20	

Run Specs	
Start Time	2020
Stop Time	2070
DT	1/20
Fractional DT	True
Save Interval	0.05
Sim Duration	0.5
Time Units	years
Pause Interval	0
Integration Method	Euler
Keep all variable results	True
Run By	Run
Calculate loop dominance information	True
Exhaustive Search Threshold	1000

Array Dimension	Indexed by	Elements
Age_Groups	Label (10)	Group_0_to_9 Group_10_to_19 Group_20_to_29 Group_30_to_39 Group_40_to_49 Group_50_to_59 Group_60_to_69 Group_70_to_79

		Group_80_to_89 Group_90_to_100
Health_Personnel	Label (2)	Nurses Specialized_doctors
Health_Personnel2	Label (2)	Nurses_1 Specialized_Doctors_2